5.4 Energy Reliability and Management

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Nomenclature

A,B	state space matrix
ACH	air change per hour
ACHP	air coupled heat pump
ADR	active demand response

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AR	(kW)	alternative resource
Arb		arbitrage
ASAI	(pu)	average service reliability index
ASIDI	(h)	average system interruption duration index
ASIFI	(pu)	average system interruption frequency index
CAES		compressed air energy storage
CAIDI	(h)	customer's average interruption duration index
CAIFI	(pu)	customer's average interruption frequency index
CCDF		composite customer damage function
CCGT		combined cycle gas turbine
CEMIn	(pu)	customer experiencing multiple interruptions
CEMSMIn	(pu)	customer experiencing multiple sustained interruptions and momentary interruptions events
CENI	(pu)	customers experiencing none interruptions
$c_i(r_i)$	(\$)	cost for the outage duration r_i
CN	(pu)	total number of customers who experienced a sustained interruption
$\mathrm{CN}_{k>n}$	(pu)	total number of customers who experienced more than n sustained interruptions
$\mathrm{CO_2}T_{i,j}$	\$	emissions costs
COP	(pu)	coefficient of performance
CPP	(\$/kWh)	critical peak pricing
CTAIDI	(h)	customer's total average interruption duration index
cur_j	(pu)	curtailment
D	(h/occurrence)	duration
d_j^{fix}	(kW)	fixed electricity demand profile
$d_j^{H,\mathrm{fix}}$	(kW)	fixed electricity demand from electric heating systems
$d_j^{H,\mathrm{var}}$	(kW)	variable electricity demand from electric heating systems
$\hat{d}_j^{H,\mathrm{var}}$		variable electricity demand from electric heating systems as stochastic variable
DG		distributed generation
DHW		domestic hot water
DR		demand response
DRR	(pu)	demand recovery ratio
DSM		demand side management
ECOST	(\$/year)	expected interruption costs
EDLC	(h/year)	expected duration of load curtailment
EENS	(kWh/year)	expected energy not served
EER	(kWh/year)	expected energy retrieved
EES		electric energy storage
EEUI	(kWh/occurrence)	expected energy unserved per interruption
EFLC	(occurrence/year)	expected frequency of load curtailment
e_h	(kW)	difference between load and generation capacity
EID	(h/occurrence)	average interruption duration of deferred loads
EIF	(occurrence/year)	average interruption rate of responsive loads
EPE	(kWh/year)	expected energy of deferred loads
ESS		energy storage system
EV		electric vehicles
ESWE	(kWh)	expected surplus wind energy
EWES	(kWh)	expected wind energy supplied
F	(occurrence/year)	frequency
FBES		flow batteries energy storage
$\mathrm{FC}_{i,j}$	\$	fuel costs
FC-HES		fuel cells–hydrogen energy storage
FES		flywheel energy storage
f_h	occurrence	frequency of load greater than generation capacity
FOR	(pu)	forced outage rate
$g_{i,j}^{\mathrm{PP}}$	(kW)	power plant output
g_j^{RES}	(kW)	renewable power plant output

h	(h)	hour
HL		hierarchical level
hor	(h)	optimization horizon
i		number of interruption states
IALSD	(h)	island average load shedding duration
IEAR	($/kWh)	interrupted energy assessment rate
IEED	(kWh/occurrence)	island expected energy deficiency
IEEI	(kWh/occurrence)	island expected energy interrupted
ILOLP	(pu)	island loss of load probability
ILSE	(kWh/occurrence)	island load shedding expectation
ISO		independent system operator
j	(h)	hourly time step
Li	kVA	kVA load interrupted for each event i
LOEE	(kWh/year)	loss of energy expectation
LOLD	(h/occurrence)	loss of load duration
LOLE	(hours/year)	loss of load expectation
LOLF	(occurrence/year)	loss of load frequency
LOLP	(occurrence/year)	loss of load probability
Lt	kVA	total kVA load served
MAIFI	(pu)	momentary average interruption frequency index
MAIFIe	(pu)	momentary average interruption event frequency index
m_i	(kW)	load curtailed
MO		merit order
nb		number of buildings
N_i	(pu)	number of interrupted customers for each event i
NSR		non-spinning reserve
N_t	(pu)	total number of customers
OCGT		open cycle gas turbine
p^{DR}	(pu)	DR participation rate
P_j^{HP}	(kW)	heat pump power
P_j^{AUX}	(kW)	auxiliary heater power
PCM		phase change material
PHES		pumped hydro energy storage
pp		percentage point
PV		photovoltaic
q_j^{DHW}	(kW)	DHW demand
q_j^{I}	(kW)	internal heat gains
q_j^{S}	(kW)	solar heat gains
r	(h/occurrence)	mean duration under outage condition or restoration time
Rc	(pu)	relative operational costs
$\mathrm{RC}_{i,j}$	$	ramping costs
REDR	(pu)	renewable energy dispatch ratio
Ref		reference
Reg		regulation
REP	(pu)	renewable energy penetration
RES		renewable energy sources
RTP	($/kWh)	real time pricing
RTS		reliability test system
RUS	(h)	rural utility service
s	(h/occurrence)	component's mean duration in service
SAIDI	(h)	system average interruption duration index
SAIFI	(pu)	system average interruption frequency index
$\mathrm{SC}_{i,j}$	$	start-up costs
SR		spinning reserve
TES		thermal energy storage
t_h	(h)	time when load is greater generation capacity

T_j	(°C)	temperature vector
$T_j^{\min}$	(°C)	comfort constraint minimum temperature
$T_j^{\max}$	(°C)	comfort constraint maximum temperature
$T_{e,j}$	(°C)	ambient air temperature
$T_{g,j}$	(°C)	ground temperature
TOC	($)	total operative costs
TOU	($/kWh)	time of use
U	(h/year)	unavailability
UC		unit commitment
UCRB	(pu)	unit cost reliability benefit
WS		wind source
WUF	(pu)	wind utilization factor
δ^{NP}	MW	nonproportional component of the stochastic variable
ε		probability that the UC schedule is inadequate to meet the load
λ	(occurrence/year)	failure rate
σ^{NP}		standard deviation of the nonproportional component, δ^{NP}

5.4.1 Introduction

Nowadays the electric power sector is experiencing an increasing production of electricity by means of renewable energy sources (RES) and also distributed generation (DG) is assuming an important role, competing with conventional baseload plants placed in a few production sites. In 2014, 13.8% of the world total primary energy demand was met with energy produced from distributed renewable sources [1]. These aspects affect the operation of the power system and especially its reliability [2]. Indeed, DG creates challenges for the management of the network, for example, with respect to local congestion and voltage problems, as the network is generally operated in different conditions from those specified in the network design phase. Intermittent RES may introduce uncertainty in the available production capacity and require backup power and energy storage systems (ESS) to ensure a reliable power supply. Furthermore, the growing world energy demand [3] reduces the capacity margins. Such variability and uncertainty on the supply side may reduce the adequacy and security of the power system. Osborne and Kawann [4] propose possible ways to improve the reliability of the electricity systems addressing the supply or the demand side. On the supply side, it is possible to intervene at the generation or at the transmission level. They state that siting new generation capacity has a central role, while it is ever more difficult to find the right place close to the growing loads [4]. For DG and RES, instead, new standardized protocols for interconnection are of paramount importance to support the advent of these technologies. At the transmission level it is necessary to (1) improve grid utilization by means of network management and load forecasting; (2) improve resource sharing with interconnected utilities; (3) develop planning instruments, for example, monitoring and control systems, regulatory frameworks, make information about reliability publicly available; and (4) organize outage management by means of a maintenance schedule or introducing penalties to fine failures. On the demand side, energy management (demand side management, DSM) strategies can help to match demand and supply, boosting the reliability of power systems [4]. Among DSM techniques, demand response (DR) may offer a valuable contribution to the reliability of a power system. DR programs perform load shifting by means of variable electricity prices or incentives that induce the final user to modify his demand load shape on the basis of the requests from, for example, the power system operator. DR is recognized as an instrument providing peak shaving, arbitrage, and regulation services in a power system [5]. Indeed, DR allows load to follow RES based generation, limiting the variability of the residual load (i.e., the load corrected for the available RES based generation) of the power system. As a consequence, DR can help to improve both the power system adequacy and security. All controllable electrical loads can be addressed by DR programs, however, the residential sector has a central role, given its big share in the overall energy consumption. It accounts for about 40% of the total energy consumption both in Europe and in the US [6,7]. Heating and cooling in buildings and industry represent half of the EU's energy consumption [8]. Moreover, the electricity demand for providing heating and cooling in buildings is foreseen to increase in the near future, given the ongoing electrification of this sector, as demonstrated by the growth of the heat pump market (about 7 million units in the EU in 2013) [9].

Furthermore, it is worth mentioning that recently, in a broader perspective, the importance of the reliability concept is reinforced by the advent of integrated energy systems, consisting in multicarrier energy systems characterized by a mutual dependence among the infrastructures of the different systems. Reliability is a key point to take into account when assessing the interdependence among different forms of energy [10]. The redundancy due to the interconnection of the systems has generally a positive impact on reliability [11]. In particular, it is important to consider the dynamic behavior of thermal loads in these systems, because their flexibility allows smaller size of the components involved in the integrated system [12]. Once

more, thermal and electrical flexibility appear strictly connected and this reinforces the link between DR and electric thermal loads, as stated above. The appeal of such kind of applications is also demonstrated by existing utilizations of this principle, as in the case of smart thermostats regulating the peak hour consumption in order to optimize comfort and energy savings [13].

Given the significance of reliability evaluations specifically for a power system, in this chapter, an innovative aspect of this concept is analyzed. Namely, the role of demand side energy management and particularly of DR to improve the reliability of a power system is investigated. In general, both reliability and DR have their own fields of application and objectives. In this piece of work the focus is given especially to the interaction of these two concepts: how can DR affect the reliability of a power system? A qualitative discussion is provided, supported by the comprehensive analysis of case studies.

The remainder of this chapter is organized as follows: Section 5.4.2 illustrates the fundamentals about reliability and energy management. Firstly, definitions of reliability and reliability assessment methods are provided. Secondly, the relationship between reliability and energy management (both on supply and demand side) is pointed out through a thorough review of the state of the art in the field. Section 5.4.3 introduces the definition and theory about DR. In addition, some critical findings available in the literature about the interdependence between DR and reliability are provided. In Section 5.4.4 the model used to support the analysis is illustrated, while the details about the considered case studies, in which DR with electric heating systems is leveraged to provide arbitrage, peak shaving, and regulation services, are described in Section 5.4.5. A qualitative discussion of the results is given in Section 5.4.6, where also a comparison with results from other methodologies is included. Future research opportunities are highlighted in Section 5.4.7 and finally closing remarks are formulated in Section 5.4.8.

5.4.2 Fundamentals

5.4.2.1 Reliability Definition

The reliability of a power system is defined as "the degree of performance of the elements of the bulk electric system that results in electricity being delivered to customers within accepted standards and in the amount desired" [14]. In other words, reliability is a measure of the ability to deliver electricity to all customers at any time. Reliability of a power system is composed of two basic aspects: adequacy and security [15]. More specifically, according to the North American Electric Reliability Council definition [14], adequacy is "the ability of the electric system to supply the aggregate electrical demand and energy requirements of the customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements," whereas security is "the ability of the electric system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system elements." Therefore, adequacy takes into account the availability of all the necessary facilities/resources to generate the demanded electricity and to deliver it to the customers. It does not consider the effect of unexpected disturbances that can affect the elements of the electric system, which are, instead, related to the concept of security. Generally, adequacy is particularly relevant for long-term planning and investments, while security typically refers to short term operation, as exemplified in **Fig. 1** [16].

Reliability studies are conducted accordingly to the relative functional zone of the power system: generation, transmission, and distribution [15]. Precisely, power system reliability studies can be classified as specific, if they deal with a specific part of the power system, or as integrated, if they take into account the relationships among different subsystems [16].

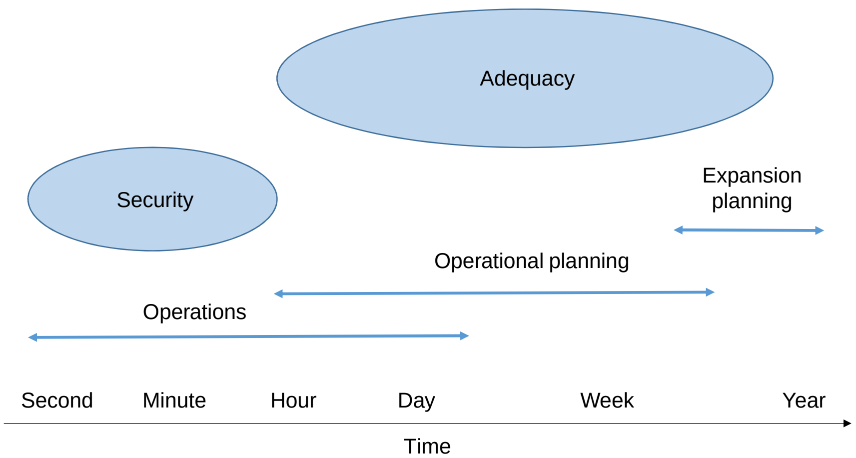

Fig. 1 Reliability analysis time frame. Inspired by Schilling MT, Do Coutto Filho MB, Leite da Silva AM, Billinton R, Allan RN. An integrated approach to power system reliability assessment. Electr Power Energy Syst 1995;17:381–90.

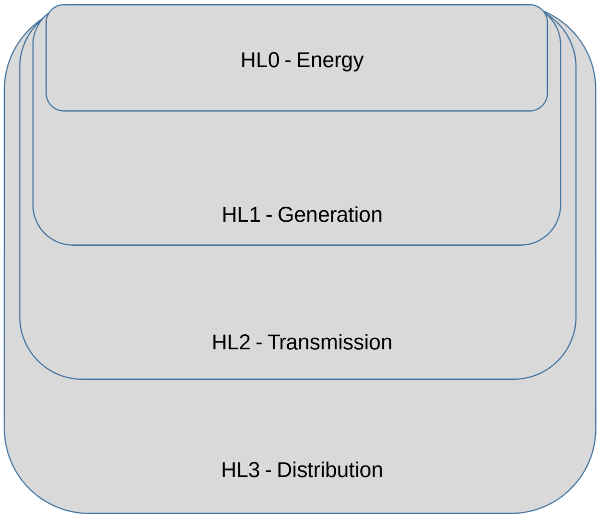

Fig. 2 Hierarchical levels of reliability analysis. Inspired by Schilling MT, Do Coutto Filho MB, Leite da Silva AM, Billinton R, Allan RN. An integrated approach to power system reliability assessment. Electr Power Energy Syst 1995;17:381–90.

A reliability assessment can be classified according to "hierarchical levels" at which the analysis is targeted (**Fig. 2**) [16]:

- HL0 – Energy: at this stage the subject of the study is just a preliminary balancing of energy demand and available electricity generation capacity of the entire electric power system (for this reason a specific metric related to HL0 does not exist, as described below).
- HL1 – Generation: it is a generating capacity reliability evaluation, aimed at assessing the adequacy of the generation system with respect to the total load requirement.
- HL2 – Transmission: it is a bulk transmission system evaluation that indicates the ability of the system to deliver the energy demanded to the transmission load points.
- HL3 – Distribution: the range of the analysis is widened to incorporate also the distribution system and the ability of the system to serve final users with the required energy is considered.

5.4.2.2 Reliability Assessment

Reliability is quantified by means of several indices, which vary according to the above mentioned hierarchical levels of the analysis.

5.4.2.2.1 Generation (HL1)

At the first level HL1, the evaluation concerns only the electricity generation facilities. Combined, these units must represent sufficient capacity to cover the electricity demand at each moment of the year and to allow scheduled maintenance. Both specific generation elements and system indicators are used:

- Frequency (F): is the frequency that an element goes from the service state to the outage state

$$F = s \cdot \lambda/(s + r) \tag{1}$$

  where s is a component's mean duration in service, r is the mean duration of the outage condition, and λ is its failure rate [17].
- Duration (D): is the average duration that an element is in its outage condition [17]

$$D = r/(s \cdot \lambda) \tag{2}$$

- Unavailability (U) or forced outage rate (FOR): is the probability that an element is in the outage condition of an element [17]

$$\mathrm{FOR} = F \cdot D = r/(s + r) \tag{3}$$

- Loss of load expectation (LOLE): represents the number of hours per annum in which it is expected that supply will not meet demand [18]. It depends on all those aspects that can affect the balance between supply and demand (e.g., a consistent number of power plants not working on a given occasion, etc.)

$$\mathrm{LOLE} = \sum_{h=1}^{8760} t_h \tag{4}$$

  where t_h is 1 when load is greater than the available electricity generation capacity and zero otherwise [19].

- Loss of energy expectation (LOEE) (some authors also call it expected energy not supplied (EENS), see Section 5.4.2.2.2) measures the expected unsupplied energy when the demand exceeds the available electricity generation capacity. It gives an idea of the severity of shortages but not of their frequency and duration, represented, instead, respectively, by loss of load frequency (LOLF) and loss of load duration (LOLD) defined below. LOEE is influenced by static conditions, such as power plant size and type, availability, maintenance requirements, load profile and its uncertainty. Neither the LOLE nor the LOEE normally include operational considerations (e.g., spinning reserve requirements, dynamic and transient system disturbances, etc.), therefore they cannot be considered as absolute measures of power system reliability [20]. LOEE is expressed as

$$\mathrm{LOEE} = \sum_{h=1}^{8760} e_h \tag{5}$$

where e_h is the difference between load and the available electricity generation capacity when the load is greater than the electricity generation capacity, or zero otherwise [19].

- LOLF: is the number of times per annum that the demand cannot be satisfied with the available electricity generation capacity:

$$\mathrm{LOLF} = \sum_{h=1}^{8760} f_h \tag{6}$$

where f_h is 1 when load is greater than generation capacity at time h and zero at time $h-1$, otherwise it is zero [19]. The loss of load probability (LOLP) is defined similarly.

- LOLD: is the average duration of an event in which the demand exceeds the available electricity generation capacity [18]:

$$\mathrm{LOLD} = \frac{\mathrm{LOLE}}{\mathrm{LOLF}} \tag{7}$$

5.4.2.2.2 Transmission (HL2)

At the HL2 stage, the framework used in the HL1 evaluations is extended to include the transmission system. Two sets of indices exist: the load point indices and the overall system indices. They are complementary and not alternatives. The load point indices show the effect on individual bus bars and provide inputs to the next hierarchical level. The system indices, instead, give an assessment of the overall adequacy. Among them, conceptually similar to their corresponding indices in HL1, there are: EENS, expected frequency of load curtailment (EFLC), expected duration of load curtailment (EDLC) [18]. Even if at this level more realism is included by considering the bulk transmission system, the evaluations typically do not take into account the power system dynamics [21].

The redundancy of individual links in transmission networks is critical because the effects of transmission disturbances may be much more widespread than the effects of distribution disturbances. Furthermore, an extensive transmission network can enhance competition in wholesale electricity markets by enabling consumers, retailers, and generators to access distant, but cost-effective sources of electricity generation, lowering the overall cost of electricity generation [4].

5.4.2.2.3 Distribution (HL3)

The third hierarchical level, HL3, includes the reliability assessment of the overall system (generation, transmission, and distribution, terminating at the customer's individual load points). However, due to the complexity of the problem, at this stage the distribution system is generally investigated as a separate entity using the HL2 load points indices as input values. Indeed, the distribution system is that part of the electric power system that connects the bulk transmission system load points to the customers. Such connections are often radial in nature and susceptible to outages due to a single event. It has been found that 80% of all interruptions at the consumer's level occur due to failures in the distribution system [22]. From the consumer's perspective, transmission and distribution related outages are most important to real-time reliability (system security). Generation and other system component outages are typically most significant to system planners, because they tend to affect the reliability of the electricity system as a whole [4]. However, proper operational planning (e.g., maintaining sufficient regulation services) allows fully mitigating the effects of outages at the supply side, limiting their impact on end consumers.

The primary indicators of the load points of distribution system are (similarly to the indices for generation facilities) [22]:

- Failure rate, λ: is the failure frequency of load point

$$\lambda = \sum \lambda_i \tag{8}$$

where i is the number of interruption states.

- Outage time, r: is the average load point duration of a failure

$$r = \frac{\sum \lambda_i \cdot r_i}{\sum \lambda_i} \tag{9}$$

- Annual outage time, U: is the annual unavailability of the load point

$$U = \lambda \cdot r \tag{10}$$

The above mentioned factors are important for the analysis of a particular load point, but they do not give any information about the overall distribution system. They are useful to calculate other system indices for reliability of distribution network in electric power systems, as defined by the IEEE guide [23].

- System average interruption frequency index (SAIFI): it provides information about the average frequency of sustained interruptions per customer over a predefined area.

$$\mathrm{SAIFI} = \frac{\sum N_i}{N_T} \tag{11}$$

- System average interruption duration index (SAIDI): it provides information about the average time the customers are interrupted.

$$\mathrm{SAIDI} = \frac{\sum r_i N_i}{\sum N_T} \tag{12}$$

- Customer average interruption duration index (CAIDI): it represents the average time required to restore service to the average customer per sustained interruption.

$$\mathrm{CAIDI} = \frac{\sum r_i N_i}{\sum N_i} = \frac{\mathrm{SAIDI}}{\mathrm{SAIFI}} \tag{13}$$

- Customer's total average interruption duration index (CTAIDI): it represents the total average time in the reporting period the customers who experienced an interruption were without power (customers that experienced multiple interruptions are counted only once).

$$\mathrm{CTAIDI} = \frac{\sum r_i N_i}{CN} \tag{14}$$

- Customer's average interruption frequency index (CAIFI): it gives the average frequency of sustained interruptions for those customers experiencing sustained interruptions (customers are counted once regardless of the number of times interrupted).

$$\mathrm{CAIFI} = \frac{\sum N_i}{CN} \tag{15}$$

- Average service availability index (ASAI): it represents the fraction of time (often in percentage) that a customer has power provided during the defined reporting period.

$$\mathrm{ASAI} = \frac{N_T \cdot h - \sum r_i N_i}{N_T \cdot h} \tag{16}$$

- Average system interruption frequency index (ASIFI): it gives information on the system average frequency of interruption, but it is based on load rather than number of customers.

$$\mathrm{ASIFI} = \frac{\sum L_i}{L_T} \tag{17}$$

- Average system interruption duration index (ASIDI): it provides information on system average duration of interruptions.

$$\mathrm{ASIDI} = \frac{\sum r_i L_i}{L_T} \tag{18}$$

- Customers experiencing multiple interruptions (CEMIn): it is designed to track the number of sustained interruptions n of a specific customer.

$$\mathrm{CEMI}_n = \frac{CN_{k>n}}{N_T} \tag{19}$$

- Rural Utility Service (RUS): it is used to determine the average outage hours for customers in rural areas. These customers may experience longer recovery periods from disturbances than other customers do because of the lower density of loads along rural feeders.

$$\mathrm{RUS} = \frac{\sum r_i}{CN} \tag{20}$$

The parameters used in the above definitions are as follows: N_i is the number of interrupted customers for each interruption event during reporting period; N_T is the total number of customers served for the area being indexed; r_i is the restoration time for each interruption event; CN is the total number of customers who have experienced a sustained interruption during the reporting period; h is the number of hours per year; L_i is connected kVA load interrupted for each interruption event and L_T is total connected kVA load served; and $CN_{k>n}$ is the total number of customers who have experienced more than n sustained interruptions during the reporting period.

Similarly, for momentary interruptions (lasting less than 5 min) other indices are defined [23], namely: momentary average interruption frequency index (MAIFI), momentary average interruption event frequency index ($MAIFI_E$), and customers experiencing multiple sustained interruptions and momentary interruption events ($CEMSMI_n$).

5.4.2.2.4 Calculation methods

The methods to calculate the reliability indices are classified in analytical methods and simulation techniques. Analytical techniques represent the system by means of a mathematical, probabilistic model to calculate the aforementioned indices. Commonly used analytical techniques are, among others, fault tree analysis, failure mode and effect analysis, minimal path methods, minimal cut methods, and fault traversal algorithm [24]. Analytical models have been widely used, but their applicability is limited for complex systems. Simulation methods instead estimate the reliability indices by simulating a stochastic behavior of the actual process. They include Monte Carlo simulation, artificial neural networks, and nonexponential distribution methods [24]. Simulation methods may require large amounts of computing time; on the other hand they can include any system effect and allow estimating probability density functions that describe, for example, the probability of load shedding. Each technique has its merits and applications and sometimes there are methods that combine both approaches (i.e., analytical and simulations techniques). Moreover, due to the uncertainties in data required to support the studies (load, failure rates, restoration time, etc.), absolute reliability metrics are typically not attainable [15]. It is of paramount importance that the data collected for performing such analysis are sufficiently comprehensive, but at the same time restrictive enough to exclude irrelevant events [21].

The IEEE reliability test system (IEEE-RTS) has been developed to satisfy the need for a standardized data base to test and compare results from different power system reliability evaluation methodologies [25].

5.4.2.2.5 Economic implications

The concept of reliability is strongly related to the economics of a power system. Generally speaking, increased reliability normally requires higher investment costs, while maintenance and damage costs decrease when reliability is improved. Customers' satisfaction is therefore augmented and as a consequence energy demand, then specific system costs (per energy unit) decrease [24]. In order to set the optimal level of reliability, a benefit–cost analysis is necessary, where the adequacy costs are compared to the value associated with adequacy (adequacy "worth": the benefit derived by the utility, customers, and society). Such assessment requires the determination of worth from the customers' perspective. These benefits are difficult to quantify; generally a common approach is an indirect evaluation of the costs associated with supply interruptions. These costs depend both on customer type and interruption characteristics. The main methodology used to assess direct short term outage costs is the customer's survey method [26]. These surveys are designed to quantify the monetary losses that would be sustained under certain specific scenarios of interruption and the willingness to pay in order to avoid them. Data collected are used to estimate composite customer damage functions (CCDF), which represent the overall average cost of interruptions as a function of the interruption duration in a given service area. Alternatively, probability distribution methods can be used to model the outage costs [26]. Reliability worth index has been introduced, interrupted energy assessment rate (IEAR), which links the EENS and outage costs:

$$\mathrm{IEAR} = \frac{\mathrm{ECOST}}{\mathrm{EENS}} \tag{21}$$

expressed in $/kWh. ECOST represents the expected interruption costs due to all possible load curtailment outage events:

$$\mathrm{ECOST} = \sum_i c_i(r_i)\lambda_i m_i \tag{22}$$

where m_i is load curtailed due to capacity shortfall, λ_i is the frequency of outage event i, r_i is duration of outage event i, $c_i(r_i)$ is cost of outage duration r_i expressed by the CCDF function [26]. In conclusion, the IEAR metric provides a monetary evaluation of the energy deficiency from the point of view of the customer.

5.4.2.2.6 New metrics

Considering the recent changes in power systems worldwide, in particular the inclusion of more renewable sources in the generation mix, the advent of DG, and the development of microgrids, new metrics have been suggested to characterize the reliability of power systems under these conditions.

For example, Karki and Billinton [27] introduced indicators to assess the effect of wind power penetration in existing power systems. Even if these indicators do not represent directly the reliability, they can be related with it because they characterize a renewable source penetration. They are the expected wind energy supplied (EWES) and the expected surplus wind energy (ESWE). EWES measures the conventional fuel energy offset by wind application and can be used to assess fuel cost and emission penalty cost savings. ESWE, instead, is defined as the amount of wind energy available but not utilized. The ratio between EWES to the total energy produced by wind turbines is called the wind utilization factor (WUF).

Whereas, Wang *et al.* [28] defined new metrics to assess the reliability of microgrids, containing RES based generation, in distribution networks. They include operational indices related with reliability in island mode, indices reflecting the DG and load characteristics, economic indices, and customer based reliability indices. Some of the proposed indices (evaluating directly or indirectly reliability issues) are listed below [28]:

- Island loss of load probability (ILOLP): the fraction of time that load demand is not satisfied during microgrid island mode.

- Island expected energy deficiency (IEED): average energy deficiency during island mode due to hours when island load exceeds total available island power generation capacity.
- Island expected energy interrupted (IEEI): expected load energy interrupted during island mode of a microgrid due to a deficiency of available generation capacity.
- Island load shedding expectation (ILSE): the average kW load that is shed during each interruption in island mode.
- Island average load shedding duration (IALSD): the average load interruption duration in island mode.
- Renewable energy penetration (REP): the percentage of demand covered by renewable energy in a microgrid in 1 year.
- Renewable energy dispatch ratio (REDR): the maximum ratio of renewable energy generation output over the total dispatchable power generation in order to maintain the stability of a microgrid.
- Unit cost reliability benefit (UCRB): the ratio of the reliability benefit to the generation cost of a microgrid.
- Customers experiencing no interruption (CENI): the percentage of microgrid CENI at all, normally on an annual basis.
  Other indices are:
- Expected energy retrieved (EER) [29]: it is designed to quantify flexible reliability.

$$\mathrm{EER} = \mathrm{AR}\, r\, \lambda \tag{23}$$

  where AR is the amount of available alternative capacity resource in a load point for a given failed element.
- Expected energy unserved per interruption (EEUI) [30]:

$$\mathrm{EEUI} = \mathrm{EENS}/\mathrm{LOLF} \tag{24}$$

- For the interruption of responsive loads in DR programs Safdarian *et al.* [31] introduced average interruption rate of responsive loads (EIF), average interruption duration of deferred loads (EID), and expected energy of deferred loads (EPE).

5.4.2.3 Energy Management and Reliability

Among the ways to improve reliability, those that can mitigate the potential electricity system resource deficiencies have an important role. They belong to the wider category of energy management methods. Energy management "is the proactive, organized and systematic coordination of procurement, conversion, distribution and use of energy to meet the requirements, taking into account environmental and economic objectives" [32].

The energy management methodologies may be useful to guarantee the power system reliability and can be realized by employing the following different approaches that affect the supply side or the demand side (**Fig. 3**). They can be categorized, on the supply side, as backup and ESS, and as DSM strategies on the demand side. They are discussed below.

5.4.2.3.1 Backup and energy storage systems

Backup and storage systems are considered energy management technologies available on the supply side of a power system.

The increasing penetration of RES (i.e., wind and solar) in the generation mix poses the challenge of continuity of supply, because of the typical intermittent behavior of such sources. Then, renewable sources generally require an energy backup system [33]. A backup system can be a conventional generator, usually fast ramping, that steps in during an outage of another conventional generator or during unexpected availability of RES based generation [33]. Similarly, storage devices can be introduced to store the surplus electric energy during periods of low demand and/or high RES-based generation, which has to be released at a later time when the demand exceeds the available generation capacity.

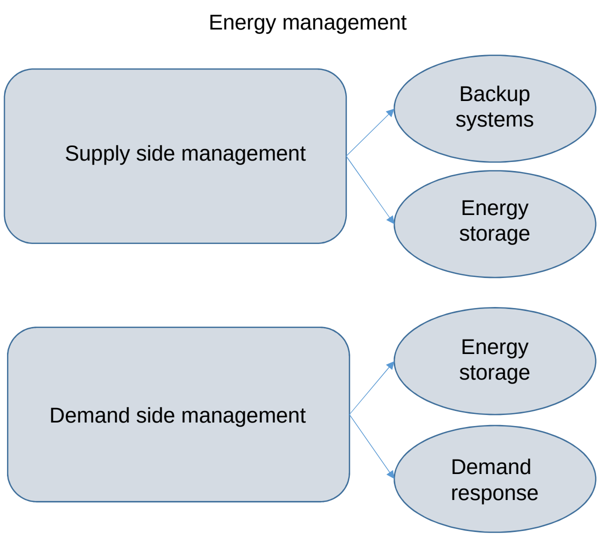

Fig. 3 Energy management technologies addressed to the supply and demand side of a power system.

Electricity storage technologies can be divided into chemical, mechanical, and thermal [34]. They can also be classified on the basis of their purpose: energy management (system adequacy) or power quality (system security) [35]. A brief description of the most relevant ones is provided below [34].

Energy management storage technologies:

- Pumped hydro energy storage (PHES): these systems use the potential energy of water, stored in two reservoirs at different height. Electric power is used to pump the water from the lower reservoir to the upper reservoir during off-peak hours. Vice versa, the water flows from the upper reservoir to the lower reservoir and passes through hydraulic turbines to produce electricity during peak times. Pumped hydroelectric systems have a good conversion efficiency, but the storage capacity is limited by the geographical constraints (elevation and available land).
- Thermal energy storage (TES): TES systems can be classified into sensible, latent, and thermochemical heat storage. In sensible TES (e.g., thermally stratified water tanks), energy is stored thanks to the variation of the temperature of the storage medium. In latent TES, during the energy storage process, phase change of the storage medium occurs, thus it is named phase change material (PCM). PCMs have the advantage of requiring smaller storage volumes, because generally latent heat is much higher than sensible heat for a substance. Moreover, the phase change occurs at nearly constant temperatures and this guarantees limited temperature variations during operation. In thermochemical TES heat can be stored also through the use of reversible chemical reactions: heat is first used to induce an endothermic chemical reaction and then it is recovered by reversing the reaction. High energy densities and long storage duration are the main features of this process.
- Compressed air energy storage (CAES): it uses electric power during off-peak hours (storage hours) in order to compress air and store it under pressure. During peak hours (retrieval hours), the pressurized air is expanded in an expansion turbine driving a generator for power production. They can be large scale (e.g., underground reservoir) or small scale (e.g., cylinders) facilities.
- Large scale batteries or flow batteries (FBES): flow batteries are composed of two chemical compounds in liquid state, separated by a membrane. This system converts chemical energy in electricity. The electrolyte is stored in external tanks and pumped into the cell when the electricity needs to be produced.
- Fuel cells–hydrogen energy storage (FC–HES): off-peak electricity is used to produce hydrogen through the electrolysis of water. Hydrogen is stored to be used later in fuel cells where a reaction between hydrogen and oxygen from the air occurs to generate electricity during peak hours.

ESS, deployed in the context of power quality management:

- Superconducting magnetic energy storage: energy is stored by means of a magnetic field created by a current that flows in a superconducting coil maintained at very low temperature.
- Flywheel energy storage (FES): a flywheel is a rotating mechanical device that is used to store rotational energy.

Several studies deal with the role of ESS to improve the reliability in a power system. These studies mainly address three topics: (1) network configuration and overall power system management, (2) photovoltaic (PV) solar power integration, and (3) wind power integration in the power system.

1. Network configuration and overall power system management: Saboori *et al.* [35] propose an optimization model to determine the location and size of ESS for reliability improvement in radial electrical distribution networks. It is shown how ESS reduce the EENS and consequently the operational costs of the system. Xu and Singh [36] present an energy storage operation strategy for a load aggregator to improve bulk power system reliability by minimizing its energy purchasing cost in a wholesale electricity market. Kahrobaee and Asgarpoor [37] analyze the role of a standby electricity storage system placed at specific load points in the network and its effect on the total reliability costs. The calculated indices in this study show the reliability improvement at both load point and system level. Arifujjaman [38] assesses the power losses (of related electrical devices), efficiency, reliability, and cost of a grid-connected energy storage system (composed of a battery and a power conversion system) for frequency regulation. This paper takes into account the conduction and switching losses of the semiconductor devices. For the case analyzed, the mean time between failures of the electric energy storage (EES) is 8 years and reliability remains at 73% after a year (considering a reliability assessing method specific for ESS). Dong *et al.* [39] present a storage and reserve sizing problem (reserve sizing is cooptimized with storage sizing to minimize the total cost of the considered microgrid) for microgrids with a high penetration of RES based generation, considering reliability indices (e.g., LOLP) within the model.
2. PV solar power integration: Koh *et al.* [40] evaluate the impact of photovoltaic systems on power system reliability at hierarchical level 1 (HL1) on the IEEE-RTS. PV panels are considered coupled with energy storage in order to improve system reliability otherwise compromised by the variability of the PV power output. The potential of PV coupled with ESS to benefit system adequacy and reduce energy cost is demonstrated. Although in this field generally battery storage systems are considered, Aihara *et al.* [41] instead propose a pumped storage power plant to mitigate the impact of PV on power system reliability. Pumped storage systems are not operated differently during daytime and nighttime as usually happens, but the operating patterns are modified in order to absorb the excess power produced by the PV systems, augmenting the power supply reliability during peak demand periods.
3. Wind power integration: with respect to wind power integration, Hu *et al.* [42] analyze the role of ESS for mitigating the potential risk related to wind power fluctuations. It is shown the importance of energy storage capacity and operational strategies during the evaluation process. Different system configurations (energy storage capacity and operating constraints, wind power dispatch restrictions, wind energy penetration level, and wind farm location) are considered to assess the impact of

Table 1 Summary of the main findings of the papers about the interaction between demand side management (DSM) and reliability

Main findings	*References*
Demand side management (DSM) reduces the optimal planning reserve margin	[56]
Total societal cost of electricity is reduced by means of DSM	[56]
DSM is beneficial for composite generation and transmission system reliability	[53]
Peak clipping strategies introduce more reliability improvements than other strategies, but they are extreme actions	[53,54]
Load shifting introduces reliability improvements similar to peak clipping strategies, but it is more easily implemented	[52,54]
Valley filling strategies have little impact on reliability because the load involved is generally low	[53,54]
Demand side load curtailment helps contingency management in restructured power systems and reduces operational costs (if interruptible loads are placed in optimal locations)	[55,57]
Load forecast uncertainty negatively influences reliability, but DSM can counteract this effect	[52,57]
Redundancy in the design of communication devices in a smart grid with DSM minimizes the cost of system failure	[59]
Web based reliability information systems are helpful for implementing DSM	[58]

energy storage on power system reliability. Moreover, Thapa and Karki [43] indicate that the energy storage potential to offset the uncertainty on wind power forecasts is limited by the rated capacity and the discharge time of the storage system. It is also shown that the storage contributes to reduce wind power curtailment. Abdullah *et al.* [44] instead propose an effective power dispatch control strategy of wind farms with integrated battery storage systems to improve the supply reliability by means of a novel scheduling algorithm using stochastic programming, taking into account the uncertainty on wind power and load forecasts. Qin *et al.* [45] discuss a reliability oriented energy storage sizing approach for wind power dominated systems, where power ratings, energy storage capacity, investment cost, and control strategy of the energy storage are all taken into account. Bhuiyan and Yazdani [46] also present a reliability assessment and components rating methodology considering a wind power system with integrated battery energy storage. They show that the battery capacity plays the most crucial role. Moreover, they suggest that the battery maximum discharging power has to be chosen slightly higher than the expected maximum load peak power, while a considerably larger value can be assigned to the maximum charging power in order to ensure rapid energy storage and higher reliability.

5.4.2.3.2 Demand side management

As explained previously, DSM is an energy management tool on the demand side. DSM is defined as "the planning, implementation, and monitoring of those utility activities designed to influence the customer's use of electricity in ways that will produce desired changes in the utility's load shape, i.e., changes in the pattern and magnitude of a utility's load" [47]. All those strategies proposed to impact the customers' use of energy are considered DSM and can be leveraged to reduce customer's demand at peak times (namely peak clipping or peak shaving), reduce energy consumption seasonally or yearly (energy conservation), change the timing of end-use consumption (load shifting) from high cost periods to low cost periods, and increase consumption during off-peak periods (valley filling) [48]. On the basis of its definition it is evident that DSM may be of paramount importance in increasing the reliability of a power system: it allows to augment the customers' satisfaction by adapting their demand to the available production. Although it has a wide definition, DSM mainly results in the implementation of three types of strategies: (1) energy efficient end-use devices; (2) energy storage; and (3) DR [49].

Among the ESS, it is worth mentioning the role of TES installed on the demand side of the power system. TES, indeed, is identified as a means for reducing peak electrical demand and high costs for electricity in peak-hours, because it can help offset the mismatch of availability of renewable electricity and demand for electricity when coupled to heating and cooling systems [50]. Whereas, DR is intended to achieve changes in customers' electrical usage in response to, for example, changes in the price of electricity over time [51]. Further details about DR are provided in the following section.

Many authors have investigated the influence of DSM strategies on power system reliability. The main findings of these works are summarized in **Table 1**.

Huang and Billinton [52], for example, analyze the impact of implementing DSM in terms of reliability benefits by applying load shifting procedures and considering load forecast uncertainty by means of Monte Carlo simulations. They prove that DSM increases the reliability and stability of the system over time. Moreover, the application of DSM tends to counteract the effects of load forecast uncertainty. Zhou *et al.* [53] estimate the impact of DSM resources on composite generation and transmission system reliability by means of Monte Carlo simulations. The DSM strategies considered are peak clipping, valley filling, strategic conservation, load shifting, and strategic load growth. Results show that DSM actions, especially peak clipping, give an important contribution to composite system reliability improvement and the reliability indices are dependent on the network topology. Huang *et al.* [54], too, test different DSM strategies and assess their impact on the adequacy of the bulk power system. Huang *et al.* [54] conclude that peak clipping has a major effect on the reliability indices but may not be practical as it reduces the energy supplied to customers. Load shifting results in a similar improvement in reliability but it is a more practical solution. Valley filling allows a system to provide more energy to customers without affecting the reliability. DG sources (e.g., wind power) provide additional generation capacity but at the same time can increase the uncertainty on the residual load profile due to their limited predictability.

Goel *et al.* [55], instead, propose a reliability assessment of restructured power systems with hybrid market models considering demand side load curtailment. The calculated reliability indices provide the expected demand curtailed for a particular customer who can be made aware of the relevance of his participation. Thus, the developed method is a possible tool for the ISO to implement the participation of customers in reliability management. Billinton and Lakhanpal [56] evaluate the impact of DSM on the reliability cost and reliability worth. The paper illustrates how the optimal planning reserve margin can vary with the introduction of DSM. Indeed, less operational reserves are needed in presence of DSM. Moreover, the total societal cost of electricity generation is reduced by the introduction of demand side activities. Yousefi Ramandi *et al.* [57] show that using interruptible loads, together with spinning reserves offered by conventional generation units, improves the reliability of a power system including wind farms, when the interruptible loads are placed in optimal locations, and reduces the expected system cost. A wind dominated system is also considered by Choi *et al.* [58]. Choi *et al.* demonstrate the role of a web-based monitoring system as an instrument to observe power system reliability. Niyato *et al.* [59] study a reliability assessment of wireless communications system in a smart grid environment to support DSM. The availability performance (i.e., the probability that the wireless connectivity between a smart meter and the meter data management system is available) is used to calculate the cost of failure, and redundancy design approaches are provided.

5.4.3 Application: Demand Response and Reliability

In this piece of work, the role of a specific DSM methodology, namely DR, is investigated in order to put into evidence its peculiar contribution toward the power system reliability.

5.4.3.1 Demand Response Definition

DR can be distinguished as active and passive DR. Active demand response (ADR) is defined as "changes in electric usage implemented directly or indirectly by end-use customers/prosumers from their current/normal consumption/injection patterns in response to certain signals" [60]. In contrast, passive DR is related to changes in the normal consumption/injection patterns without interacting with the consumers (e.g., rolling blackouts). Hereafter ADR will be considered and referred to simply as DR.

DR can be performed by means of price based programs and incentive based programs. A price based program induces a change in customers' load pattern by acting on time varying electricity rate. Different tariff structures exist [61]:

- Time-of-use (TOU): different tariffs are applied during different periods of time in a day. TOU tariffs ideally reflect the average cost of generating and delivering electric energy during the corresponding periods of time.
- Real-time pricing (RTP) or dynamic pricing: the retail price for electricity typically varies, for example, hourly on the basis of the wholesale price of electricity. Customers are generally notified in advance of the dynamic rate (on a day-ahead or hour-ahead basis).
- Critical peak pricing (CPP): it is a combination of the TOU and RTP tariffs. CPP is composed of TOU rates in normal times, while a peak price is used when specific critical conditions occur (e.g., when system reliability is compromised or supply prices are very high).

An incentive based program, also called reliability based DR, operates load reduction by means of monetary incentives (e.g., a discounted, but fixed electricity tariff or an annual payment to the consumer) to the customers. Typically a change in the normal energy use is requested when reliability conditions are threatened or when market prices are well above average values. If the customer enrolled in such a program fails to respond, a penalty can be applied. Possible incentive based programs are [61]:

- Direct load control: the utility remotely controls customers' electrical equipment (e.g., air conditioner, water heater) and, on short notice, it can switch them on or off on the basis of its needs.
- Interruptible/curtailable service: customers have a reduced rate if they agree to lower their demand to a certain level (curtailable rate) or even to zero (interruptible rate) during system contingencies. Typically this program is addressed to industrial or commercial customers.
- Demand bidding/buyback program: customers voluntarily submit load reduction bids to lower their load when the utility communicates the possibility to take part to a DR action, generally on a day-ahead basis.
- Emergency DR programs: customers receive incentives to reduce their loads during emergency events.
- Economic DR programs: customers are invited to reduce their load when the electricity price rises too high in spot events.
- Ancillary services DR program: customers receive incentives in exchange of load curtailment and/or fast downward ramping their demand. In this case the load modification is used as operating reserve or frequency regulation service.

5.4.3.2 Benefits and Challenges

O'Connell *et al.* [62] examine the main benefits and challenges for DR program introduction. The operating advantages, widely recognized in the literature, are mainly related to the DR program's ability to increase the flexibility and overall reliability of the entire system [62]. Indeed, by altering the energy demand over time, DR allows matching the demand with the available electricity production. This is particularly useful in a power system including limited predictable and intermittent electricity generation from

renewable resources, for example, wind and solar power. Moreover, customers taking part in a DR program can provide fast response to the requests received from, for example, the grid operator. DR may reduce the need for interconnections with neighboring power systems. From a system planning point of view, DR may reduce the necessity for new generation capacity. The geographical diversity of the customers may help to solve congestion problems and reduce the need for network upgrades. Eventually, from an economic point of view, DR may lower the overall costs of a power system, even if the benefit for a singular customer can be very limited, especially when a wide participation in the DR program is foreseen [63].

For O'Connell *et al.* [62], the main challenges, instead, for the effective uptake of DR are related to the lack of proper market mechanisms for its realization and also to the difficulty in controlling and interacting with the customers involved. At present, DR is primarily employed for the provision of emergency contingency support and ancillary services, with limited participation in the day-ahead market. Moreover the actual tariff structures are not always very clear, which may make it difficult to make the customer aware of the advantage of taking part in a DR program. With the introduction of DR, the customer becomes an active player in the energy market and shares the responsibility for maintaining system security. Customers could be exposed to extremely high or fluctuating prices if no protecting mechanisms are put in place. Furthermore, it is difficult to control and predict the final users' behavior: they could always decide not to participate into the program, causing reliability issues in the overall system [62]. Summarizing, the main efforts to push the uptake of DR programs have to be aimed at removing the regulatory, market, and technology (e.g., smart metering, communication networks, and automated control technologies) barriers and at improving customer knowledge and acceptance of DR [61].

5.4.3.3 Demand Response Loads and Simulation Tools

DR programs can be addressed to big commercial and industrial customers, but also to residential customers. In this context it can act on deferrable loads (e.g., dishwashers, laundry machines, etc.) or thermostatically controlled loads (heat pumps, refrigerators, and air conditioners). The last category is particularly relevant taking into account the big share of the total energy demand that comes from buildings and in particular from their cooling/heating needs [50]. The built environment offers an important possible field of application for DR and it is also practically easily implementable: load shifting of heating/cooling devices can be attained via intelligent control strategies, without loss of thermal comfort for the user, thanks to the inherent thermal storage that a building can offer [63].

In order to assess the real contribution that a DR program can provide to a power system, it is of paramount importance to use proper simulation models. They can be classified into models focused on the supply side (e.g., price-elasticity models, virtual generator models), models focused on the demand side (using a fixed price profile), and integrated models. Only integrated models allow to represent in a detailed way both the demand and supply side and to take into account their real interaction. In fact, when customers react to a price signal by shifting their demand, as a consequence they affect the price signal, reflecting the new energy demand–supply balance. Neglecting such interaction could lead to erroneous conclusions about the potential financial gains associated with DR [64].

5.4.3.4 Demand Response and Reliability: State of the Art

In this section the state of the art on the relationship between reliability and DR is thoroughly analyzed. DR can be used within the context of a power system to reduce the required capacity, ancillary services, or emergency reserves [65]. Indeed, it allows load shifting, thus reducing energy consumption during peak periods, thereby postponing new generation capacity investments and/or operational reserve requirements. For this reason DR contributes to improvements of the adequacy of a power system and is defined in Ref. [62] as nonemergency DR, contributing to the capacity margin (see **Fig. 4** for the relationship between peak load, installed capacity, and capacity margin [66]). Furthermore, DR customers can be asked to curtail or shift their deferrable loads in case of emergency (namely emergency DR [65]). In this sense DR can also improve the power system security, as demonstrated by Mohagheghi *et al.* [67]. Mohagheghi *et al.* [67] discuss qualitatively the DR potential to reduce the overall system demand during peak times, providing a safety margin to the power system in case it is exposed to faults and disturbances. Moreover, they show that DR can improve the dynamic performance of the system when it allows emergency load reduction. Considering both DR attributes (allowing peak shaving and emergency reserves), its role in improving system reliability affects not only the availability of service, but also system security. This article concludes that in general power system reliability benefits from applying DR. However, a successful implementation of DR requires the usage of smart devices (sensors, meters, and actuators), which pose additional reliability considerations associated with their operation.

In order to properly evaluate DR programs, especially in case they act as emergency (or operational) reserves, it is important to define the overall duration and the development over time of a DR event (**Fig. 5**): DR customers need an advance notification (a few hours or the day ahead) to decide whether they will participate in the action requested, after which it takes a certain amount of time (ramp period) until the consumer's demand is reduced to the requested levels. After the ramp period there is the deployment of the DR resource. A transition period (recovery period) may be necessary before resuming normal operation. Ramping times are strictly related to the type of customer and they can range from a few seconds to a few minutes [67].

Below, the available papers in the scientific literature are grouped on the basis of the following classification: (1) DR related to adequacy purposes and (2) DR related to security purposes. Considering the intimate relationship between the two different

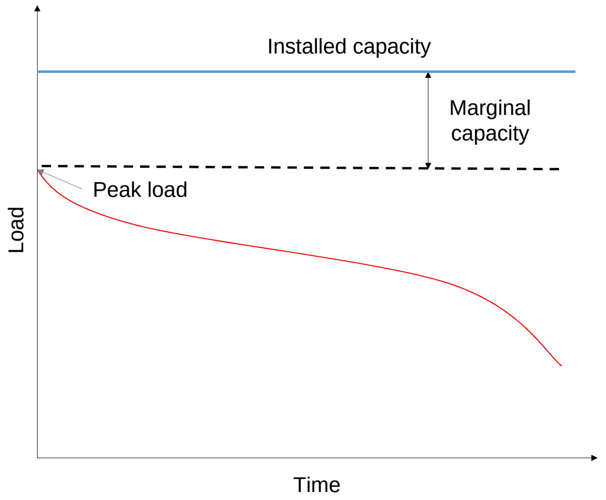

Fig. 4 Relationship among peak load, capacity, and capacity margin. Inspired by Billinton R, Allan RN. Reliability evaluation of power systems. Boston: Pitman; 1984.

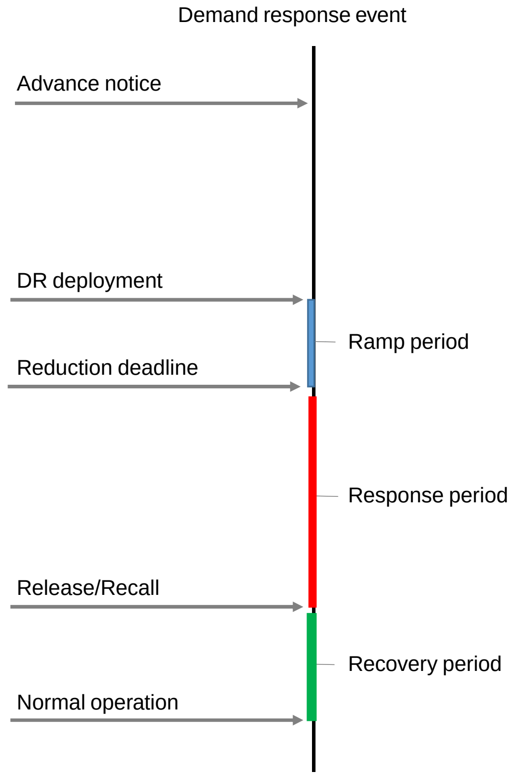

Fig. 5 Time development of a demand response (DR) event. Inspired by Lee S-S, Lee H-C, Yoo T-H, *et al.* Demand response operation rules based on reliability for South Korean power system. In: IEEE Power and Energy Society General Meeting; 2011.

aspects of reliability (i.e., adequacy and security), such categories are not always strictly separated and some studies can cover both purposes. Main findings of the available works in the scientific literature are also collected in **Table 2**.

1. DR related to adequacy: The role of customers in a DR program is of course of paramount importance. Regarding this issue, Kwag and Kim [68] evaluate the effects of DR programs taking into account the customers' behavior and particularly what happens when the DR customers fail to adhere to the scheduled demand reduction. Such a situation could potentially cause new reliability problems. In detail, the impact of customers' behaviors on the DR resource availability is represented in the same form as conventional generation units, which can be available or unavailable. It is highlighted that an improvement of

Table 2 Summary of the main findings of the papers about the interaction between demand response (DR) and reliability. Reliability category: (1) DR related to adequacy; (2) DR related to security

Category	*Main findings*	*Reference*
1	Interruptible loads at specific buses reduce considerably the total societal cost of electricity	[69]
	Direct load control improves system reliability	[70]
	Design guidelines of a real demand response (DR) program are provided	[65]
	DR has considerable impact on reliability, also with a limited customers' participation and it is better to improve the exploitation of available DR programs without increasing the amount of further initiatives	[68,71]
	DR programs, aimed at high energy demand reduction, generally do not increase system reliability	[72]
	DR causes inevitable energy payback (due to load restoration) that produces lower but longer peak loads and such effect can negatively affect system reliability	[30]
2	DR supports both availability of service by reducing peak demand and security by providing a safety margin, for example, DR helps to manage the occurrence of contingencies in generations units	[67,73,75]
	DR allows network operators to modify the system load profile, instead of shedding loads, thus improving service reliability	[31]
	DR can provide flexible reliability: high priority customers can be supplied also during contingency states	[29,77]
	DR programs counteract the negative effect of volatility of renewable energy sources on power system reliability	[74]
	DR based reliability constrained model can be used to optimize the participation of energy service providers in the electricity market	[76]

the participation in existing DR programs has a much stronger positive effect on the reliability of the power system than increasing the amount of DR initiatives. DR strategies can have a positive effect, if well designed, on the power system both using incentive based programs and price based programs, as demonstrated by several studies in the scientific literature. Fotuhi-Firuzabad and Billinton [69] present a hybrid probabilistic/deterministic technique for system reliability evaluation considering interruptible loads as a load management alternative (an interruptible load contract allows the utility to reduce the demand when requested by the utility and provides an incentive to the customers involved). The study results indicate that the interruptible load initiative has a great cost savings potential in terms of reducing the total societal cost of electricity. Azami and Fard [70] evaluate the effects of direct load control DR program on reliability indices and show that DR programs can improve the system and nodal reliability. Instead, Samadi *et al.* [71] analyze the effects of price-based (TOU) DR programs on the modification of the load demand curve and reliability. They show that DR programs reduce the peak demand, improve the load factor (ratio between actual energy consumption and maximum generation capacity), and reduce the expected energy not served. However, even if most of the DR programs improve the reliability indices, inappropriate designs of DR programs can lead to the undesirable result of reducing system reliability. Indeed, it is relevant to consider the energy demand modification after DR events, i.e., load restoration. In line with these concerns, Zhou *et al.* [30] investigate the reliability implications of deploying DR and EES systems at the system level, i.e., the consequences on the displacement of generation capacity. Results show that DR and electric energy storage (EES) can reduce the frequency and cumulative duration of interruptions, but that these interruptions – when they occur – may become more severe. It is thus of paramount importance to take into account the side effects of load restoration after voluntary load shifting. Similarly, Nikzad and Mozafari [72] quantify the impact of DR programs on the reliability of restructured power systems. An optimization model is used to determine load curtailment and generation redispatch for each contingency state and includes incentive and penalty mechanisms together with different customers' behaviors. Reliability indices for load points, generation companies, transmission network, and the whole system are calculated for the Iranian power system. Results show that programs for intensive energy reduction (one of the goals of the Iranian system operator in designing DR programs) do not always guarantee an increased system reliability.

2. DR related to security: Aghaei *et al.* [73] study the influence of emergency DR programs in improving reliability in case of failure of generation units. They demonstrate that emergency DR programs may have significant influence, even at a low DR penetration: emergency DR can both prevent price spikes in specific hours, and acts as additional reserve capacity to increase the overall reliability of the system during critical hours. Moshari *et al.* [74], instead, consider the effects of DR programs on short term reliability of wind dominated power systems. In the short term reliability assessment, the failure probabilities depend on time of occurrence and on the initial states of system components. Moreover, it is important to take into account that consumers need a certain time to successfully manage their load, thus DR programs should be announced beforehand. This work proposes a model that represents DR uncertainty and shows how the lead time of remedial resources affects the short term reliability assessment of the power system. Gaspar and Gomes [75] investigate the role of controllable demand for guaranteeing adequate reliability in short term operation of power systems. An evolution strategy to design adequate control actions is developed by the authors. It is applied over end-use loads and its impact is assessed by means of the reliability indices. Results confirm that controllable loads can be an effective alternative to reserve generation capacity.

The influence of DR on the distribution network is studied by Mahboubi-Moghaddam *et al.* [76]. They propose a decision model helpful for energy service providers. It includes DR programs and considers their effect on network reliability (assessed by

means of a failure-mode-and-effect analysis approach). The simulation results demonstrate the significant benefits of DR on the performance of such energy service providers who can, thanks to the proposed decision model, effectively take into account, in a robust manner, the DR potential and price uncertainty. A beneficial effect of increasing the customers' adherence to the DR program is discussed by Safdarian *et al.* [31]. They assess the potential impact of DR on service reliability in a residential distribution network. The analysis is based on metered hourly consumption profiles and survey data of hundreds of customers from a Finnish city. The obtained results show that great reliability improvements can be achieved by enabling DR without customers' discomfort when a sufficiently large number of customers is participating in the program.

Syrri and Mancarella [77], instead, define a particular application of DR, so called postfault DR. It relies on DR customers accepting contracts for differentiated reliability, driven by the willingness to accept lower service quality for economic benefits. Postfault DR is used along with network automation with the aim to provide congestion management. It is demonstrated that with DR the network could be stressed up to its maximum limits without compromising the reliability comfort of non-DR customers and without proceeding to network reinforcements, with a small increase in the unreliability costs. Eventually, Baboli *et al.* [29] introduce the concept of flexible reliability, meaning that, while a minimum reliability level is provided for all customers in the distribution network, there are high priority customers that are supplied also in contingency states (paying the corresponding cost). Demand side resources, including DR, are considered as instruments to operate a microgrid with such flexible reliability targets. A new index, EER, is used to quantify the effectiveness of flexible reliability approach and the results illustrate the positive impact of demand side resources.

On the basis of the state of the art review here presented, it is evident that there are a lot of implications associated with the introduction of DR programs in a power system, affecting the electricity generation system, the transmission and distribution network, and the demand side. In the following sections some of the main effects associated with the implementation of DR programs will be further explored by means of a case study, so as to make the relationship between DR and reliability even clearer to the reader.

5.4.4 Analysis and Assessment

As demonstrated by the literature review in the previous section, the influence of DR on power system reliability may be considerable. In this section, we will further illustrate this intimate relationship qualitatively by means of case studies. We employ a so-called integrated operational model, which represents both the supply side and demand side. The model is referred to as integrated, because it takes into account the interactions between the two different parts of the power system. Indeed, this interaction of electricity generation and demand cannot be neglected if one aims to account effectively for their mutual influence on the electricity price. In this model the transmission and distribution grid is not considered. In our case studies, it is assumed that DR programs are focused on residential electric heating systems (heat pumps and auxiliary electric resistances) coupled with passive (building envelope) and active (domestic hot water (DHW), storage tank) TES. The DR strategy considered is direct load control: the utility can intervene to shift the customers' electricity demand in order to optimize the overall system, i.e., to minimize the operational costs associated with meeting the demand for electricity and thermal comfort (see below).

The focus is on electric heating systems because they represent a relevant share of the total domestic electricity demand. Furthermore, the electricity demand from electric heating systems is foreseen to increase in the near future due to the increasing penetration of such systems, triggered by their good efficiency and their potential to accommodate the growing production of electricity from RES [9]. The main advantage of thermostatically controllable loads as DR resources over the other deferrable loads (e.g., dishwashers, driers, fridges, etc.) is related to buildings' inherent thermal inertia, which allows altering the electricity usage profile of the heating systems without tampering with the indoor thermal comfort. However, the assessment of this kind of DR program is a bit more complicated, because it requires taking into account the thermal behavior of the building active and passive thermal mass in a time-dependent analysis. The description of the loads that can be controlled is of paramount importance, because it affects the operational characteristics of DR and the load restoration after the DR event.

5.4.4.1 Integrated Model

The model used belongs to the group of integrated models. Such models represent both the dynamic behavior of the supply and demand side. Main advantages of this approach are (1) the electricity demand (from electric heating systems here) is close to reality, thanks to the detailed representation of the system; (2) the influence of the demand on the electricity price, and vice versa, is taken into account; and (3) it is possible to guarantee at the same time both the internal thermal comfort and the DR balancing services to the power system. On the other hand, solving these models often requires a significant computational effort, thus some simplification can be introduced, as better explained below.

In the most general formulation of the model, expressed as a mixed integer linear programming model, the supply side is represented by a unit commitment (UC) and economic dispatch (ED) model, which minimizes the overall operational costs composed of start-up costs (SC), fuel costs (FC), ramping costs (RC), and emission costs (CO_2T) (Eq. (25)):

$$\min \sum_{ij}^{\text{hor}} \text{cost}\left(g_{i,j}^{\text{PP}}\right) = \sum_i \sum_j \text{SC}_{i,j} + \text{FC}_{i,j} + \text{RC}_{i,j} + \text{CO}_2 T_{i,j} \tag{25}$$

for every power plant i at every hourly time step j over the optimization horizon, hor. The output of the power plants $\left(g_{i,j}{}^{\mathrm{PP}}\right)$ is assessed taking into account some technical constraints, such as the minimum and maximum operating point of each power plant, ramping constraints, minimum on- and off-times (Eq. (26)):

$$f\left(g_{i,j}^{\mathrm{PP}}\right)=0 \tag{26}$$

Then, the electricity produced has to equal the overall electricity demand, as shown in Eq. (27):

$$d_j^{\mathrm{fix}}+\mathrm{nb}\cdot\left(\left(1-p^{\mathrm{DR}}\right)\cdot d_j^{H,\mathrm{fix}}+p^{\mathrm{DR}}\cdot d_j^{H,\mathrm{var}}\right)=\sum_j g_{ij}^{\mathrm{PP}}+\mathrm{cur}_j\cdot g_j^{\mathrm{RES}} \tag{27}$$

where g_j^{RES} represents the available RES based generation. This electricity generation can be curtailed (cur_j) and the curtailment is assumed to be free (Eq. (28)):

$$0\leq \mathrm{cur}_j\leq 1 \tag{28}$$

In order to reduce the computational effort required to solve this problem, another formulation of the supply side is also considered in the case studies presented in the next section. It employs a so-called merit order (MO) model, which consists of a mere ranking of the different power plants in an ascending order of average operational costs. The MO model can calculate the hourly output of each power plant $\left(g_{i,j}^{\mathrm{PP}}\right)$ considering the minimum and maximum operating point of each power plant, but neglecting ramping constraints, minimum on- and off-times and SC (this affects the formulation of Eq. (26) and Eq. (27), modified accordingly). The validity of such a simplified approach in the context of DR, rather than a complete UC and ED model, has been demonstrated by Patteeuw *et al.* [64].

Regarding the electricity demand, instead, it is composed of a fixed electricity demand profile $\left(d_j^{\mathrm{fix}}\right)$ plus the electricity demand of the electric heating systems for a certain number of representative buildings (nb). The demand from the electric heating systems can be adherent to a DR scheme $\left(d_j^{H,\mathrm{var}}\right)$ or can be fixed to a predefined profile $\left(d_j^{H,\mathrm{fix}}\right)$. The share of flexible (p^{DR}) and inflexible ($1-p^{\mathrm{DR}}$) demand from electric heating systems is depicted by the parameter p^{DR}, i.e., the DR participation rate. The DR adherent demand is evaluated on the basis of a physical demand side model, representing the thermal behavior of the dwellings with the electric heating systems and thermal storage systems. This demand side model is described by Eqs. (29)–(31):

$$d_j^{H,\mathrm{var}}=P_j^{\mathrm{HP}}+P_j^{\mathrm{AUX}} \tag{29}$$

$$\sum_j T_{j+1}=A\cdot T_j+B\cdot\left[P_j^{\mathrm{HP}},P_j^{\mathrm{AUX}},q_j^{\mathrm{DHW}},T_{e,j},T_{g,j},q_j^S,q_j^I\right] \tag{30}$$

$$T_j^{\min}\leq T_j\leq T_j^{\max} \tag{31}$$

The demand from the electric heating systems (Eq. (29)) that participate to a DR scheme $\left(d_j^{H,\mathrm{var}}\right)$ is due to the heat pump $\left(P_j^{\mathrm{HP}}\right)$ or the backup auxiliary heater $\left(P_j^{\mathrm{AUX}}\right)$. They both heat the building and the DHW tank, which are represented by a state space model (Eq. (30)) with state space matrices A and B. The vector with the states (T_j) contains the temperatures of the building and DHW tank. The temperature has to be within the comfort bounds, $T_j^{\min}$ and $T_j^{\max}$ (Eq. (31)). The disturbances included are DHW demand $\left(\mathrm{q}_j^{\mathrm{DHW}}\right)$, ambient air temperature ($T_{e,j}$), ground temperature ($T_{g,j}$), solar heat gains $\left(\mathrm{q}_j^S\right)$, and internal heat gains $\left(\mathrm{q}_j^I\right)$. The same demand side model is used to assess the electricity demand of the heating systems not adherent to a DR scheme $\left(d_j^{H,\mathrm{fix}}\right)$: it is the minimum energy used to comply with the thermal demand necessary for maintaining the comfort. In such case any interaction with the supply side model is neglected ($p^{\mathrm{DR}}=0\%$). An in-depth description of the model is provided in [64].

The described model is used to assess the impact of introducing DR programs on the power system, quantified in terms of overall operational costs, RES based generation utilization, peak shaving potential, and expected load shedding volumes. In Section 5.4.5, the four case studies are presented. The results are shown in Section 5.4.6 and deal with three applications:

1. Energy management, i.e., load shifting and demand flexibility that leads to a more efficient scheduling of the electricity generation system and a higher utilization of RES based generation, resulting in operational costs reduction;
2. DR related to adequacy: DR programs may entail a significant peak shaving potential, improving the power system adequacy;
3. DR related to security: DR adherent load may offer cost effective regulation services, resulting in high reliability levels (security levels) at a lower expected operational cost.

The first application allows illustrating how the model works and what kind of results one can expect by introducing DR programs, facilitating the understanding of the relationship between DR and reliability. This intimate relationship is discussed by means of the second and third application, focusing on system adequacy and security, respectively.

5.4.5 Case Studies

Four different case studies are considered. In all of them the power system is inspired by the Belgian power system, but may consider different reference scenarios, thus different installed capacities, generation mix, and building stocks are assumed. In this

Table 3 Overview on the four case studies used in the analysis

Case study	*Supply side representation*	*Demand side representation*	*Reference scenario*	*Objective*
A	• MO model • RES 30% (50% wind and 50% PV) • Only gas fired power plants	• Good insulated buildings • Floor heating	2030	• DR energy management • DR peak shaving potential and system adequacy
B	• UC&ED model • RES 20% (50% wind and 50% PV) • Mixed fossil fueled power plants	• Buildings from the period 2005–10 • Radiators	2013	• DR energy management
C	• UC&ED model • RES 40% (30% wind & 10% PV) • Only gas fired power plants	• Different building typologies • Radiators and floor heating	2030	• DR peak shaving potential and system adequacy
D	• UC&ED model • RES 50% (wind) • Mixed fossil fueled power plants + PHES	• Good insulated buildings • Floor heating	2013	• DR short term behavior and system security • DR limited controllability

Abbreviations: DR, demand response; ED, economic dispatch; MO, merit order; PHES, pumped hydro energy storage; PV, photovoltaic; RES, renewable energy sources; UC, unit commitment.

way a broad representation of possible scenarios is possible and a wider set of results could be obtained. In the following the details of each case study are described. The main features of each case study and the objective in its analysis are summarized in **Table 3**.

5.4.5.1 Case Study A

This case study is the same as in Arteconi *et al.* [63] and has been simulated by means of the MO supply model (see Section 5.4.4.1). The electricity generation system represents a future scenario in 2030 and it is composed only of gas fired power plants as fossil based generation, with a total installed capacity of 11,200 MW combined cycle gas turbines (CCGT) and 5800 MW open cycle gas turbines (OCGT). It has been assumed that RES based electricity generation is capable of covering 30% of the electricity demand and consists of 50% solar and 50% wind energy. Both the fixed electricity demand profile $\left(d_j^{\text{fix}}\right)$ and the electricity generation from RES $\left(g_j^{\text{RES}}\right)$ are taken from the Belgian transmission grid operator [78].

Regarding the demand side, the nb is assumed to be about one million, which is the expected number of detached buildings for Belgium in 2030 [79]. An average building, taken from the TABULA project [80], is assumed as reference with a total surface area of 270 m^2, an average U-value of 0.3 $Wm^{-2}K^{-1}$, and a ventilation rate of 0.4 air changes per hour (ACH). The state space building model is based on Reynders *et al.* [81]. Stochastic profiles to represent the user behavior, namely the temperature set points and DHW demand, are employed, as suggested by [82]. The lower bounds for the indoor temperature set points are 20 and 18°C for the day zone and night zone, respectively, while the upper bounds are 2°C higher than lower bounds [83]. The DHW storage tanks are either 200 or 300 L, depending on the maximum daily hot water demand. DHW is supplied at 50°C, while the upper bound for the DHW storage tank is 60°C.

Measurements in Uccle (Brussels, Belgium) for the weather data for 2013 are used. The heating system consists of an air coupled heat pump (ACHP), which supplies heat both to the floor heating system and to the storage tank for DHW. The heat pump is sized to meet 80% of the peak heat demand. A backup electric resistance heater is also included. The coefficient of performance (COP) of the heat pump is determined according to Bettgenhauser *et al.* [84]. The nominal supply water temperature of the floor heating is 35°C. Based on this, the COP is predetermined and assumed to be constant throughout each optimization period [85]. A variable share of flexible demand from electric heating systems (p^{DR}) is considered, in order to assess its influence on the operation of the overall power system. The DR penetration can vary between 5 and 100% (for more details about the case study see Ref. [63]).

This case study is used in the following to illustrate the energy management potential of DR (Section 5.4.6.1). Furthermore it is considered to assess the impact of DR on power system adequacy, specifically on peak shaving potential (Section 5.4.6.2).

5.4.5.2 Case Study B

This case study is the same as in Patteeuw *et al.* [64]. Here the more general formulation of the model, with UC and ED representation, for the supply side is employed. In this case the reference is the present Belgian scenario. Differences with Case Study A are listed below.

The electricity generation is composed of 1 nuclear power plant (1200 MW), 5 coal-fired steam power plants (4000 MW), 10 gas-fired combined cycle power plants (CCGT, 4000 MW), and 10 OCGT and oil-fired power plants (OCGT, 1000 MW). RES-based electrical energy accounts for 20% of the generated electrical energy over the year.

Buildings characteristics refer to a typical Belgian building built between 2005 and 2010. The building considered has a floor surface of 270 m^2. Infiltration and ventilation combined cause 1.5 air changes per hour. The exterior walls, roof, and windows, respectively, have a U-value of 0.4, 0.5, and 1.4 W m^{-2} K^{-1}. The average window surface in each cardinal direction is of about 10 m^2. The electric heating system is an air source heat pump coupled in this case with radiators as emission systems.

This case study is again applied in Section 5.4.6.1 to illustrate the load shifting potential of DR. Such results, referred to the present scenario, are compared with those obtained for Case Study A, referred instead to a future scenario.

5.4.5.3 Case Study C

In this case study, the electricity generation side is represented by a so-called MO model, as discussed in [40]. The reference year for the case study is 2030. A RES share of 40% (on an annual electric energy consumption basis) is considered, divided into 30% wind energy and 10% solar photovoltaic energy. In terms of conventional generation capacity, only gas-fired power plants are considered, as in Case Study A.

The peculiarity of this case study is the detailed representation of the demand side, where 36 different building types are considered, based on results of the TABULA project [80], as discussed in Protopapadaki *et al.* [79]. These building archetypes represent the Belgian residential building stock. Three different single family buildings (detached, semidetached, and terraced houses) are taken into account, belonging to six age classes (i.e., before 1945, 1945–70, 1971–90, 1991–2005, 2006–12, after 2012), undergone to two possible renovation levels (mild or thorough). The electric heating system is represented by heat pumps coupled with floor heating systems or radiators. The penetration of this technology is assumed to be equal to 250,000 units by 2030 for each building topology, which are studied individually. A more detailed description of this case study can be found in [86].

Case Study C is used in Section 5.4.6.2 to show the effect of different building types and their corresponding heating system on peak power reduction, thus on power system adequacy.

5.4.5.4 Case Study D

The fourth case study is defined by Bruninx [5,87]. For this case study, the integrated model has been extended to include the procurement and activation of reserves, offered by the DR resource, and a possible limited controllability of the DR resource. The generation system is represented by a detailed, state of the art UC model with endogenous, probabilistic reserve sizing and activation [88]. The power system is inspired on the Belgian power system in the year 2013, complemented with eight additional 450 MW CCGTs to cover the additional electrical heating demand. In detail, the electricity generation is composed of nuclear power plants (5925 MW), coal-fired steam power plants (760 MW), combined cycle power plants (CCGT, 9575 MW) and small peaking units, such as OCGT and oil-fired power plants (1260 MW). One PHES system with a maximum storage capacity of 3924 MWh, a round trip efficiency of 75%, and a capacity of 1308 MW is included in the power system. A 50% wind energy penetration (relative to the annual energy demand) is assumed. The demand side is represented in the same way as in Case Study A, assuming that approximately 1 million households have a DR-adherent heating system ($p^{DR}=100\%$). Case study D is used in the evaluation of DR role on security of a power system (Section 5.4.6.3).

5.4.6 Results and Discussion

To allow framing the impact of DR on the reliability of the power system, Section 5.4.6.1 briefly discusses the operational impact of such DR schemes. Section 5.4.6.2 deals with DR based peak shifting as a method to increase the adequacy of a system. Short term reliability (security) and DR based reserves is the topic at hand in Section 5.4.6.3.

5.4.6.1 Energy Management and Demand Flexibility

In Fig. 6 the output of the electricity production plants obtained with the simulation model for the above mentioned Case Study A is visualized. In this case study, the electricity generation mix contains only gas fired power plants (CCGT and OCGT) and RES based generation, representing a possible future electricity generation mix. The CCGT plants are more efficient; their efficiency can vary between 50 and 60% [63], thus they are used to covering the baseload residual demand, i.e., the electricity demand from which the electricity generation from RES is subtracted. For the peak residual demand, instead, the OCGT plants are used, whose efficiency ranges between 30 and 40% [63]. Fig. 6 shows the effect of DR programs on the power output during 48 typical winter operating hours and highlights what happens when the DR participation increases (Fig. 6(A) $p^{DR}=25\%$ vs. Fig. 6(B) $p^{DR}=100\%$). It is evident that the load shifting due to the introduced DR flexibility produces valley filling over time and, consequently, reduces RES curtailment and OCGT use for peak residual demand. This increases overall system efficiency.

Fig. 7 contains, instead, results obtained with a similar simulation model (using a UC, and ED model to represent the supply side) for Case Study B [63], which show even more clearly the impact of load shifting on the use of different electricity generation

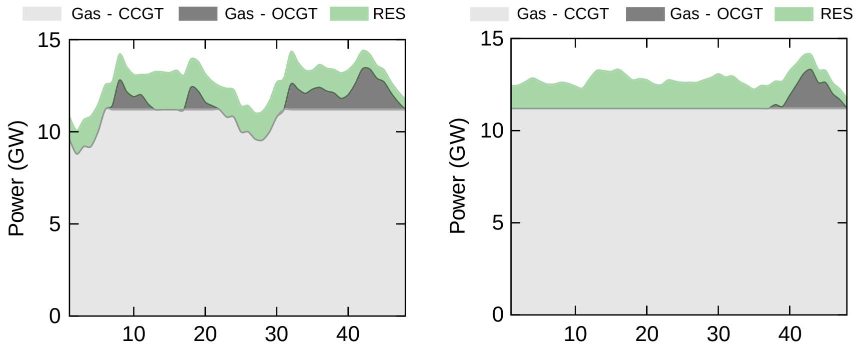

Fig. 6 Case Study A. Output of the electricity generation system (open cycle gas turbines (OCGT), combined cycle gas turbines (CCGT), and renewable energy sources (RES)) for two shares of demand response participation rate: (A) 25% and (B) 100%. Inspired by Arteconi A, Patteeuw D, Bruninx K, *et al.* Active demand response with electric heating systems: impact of market penetration. App Energy 2016;177:636–48.

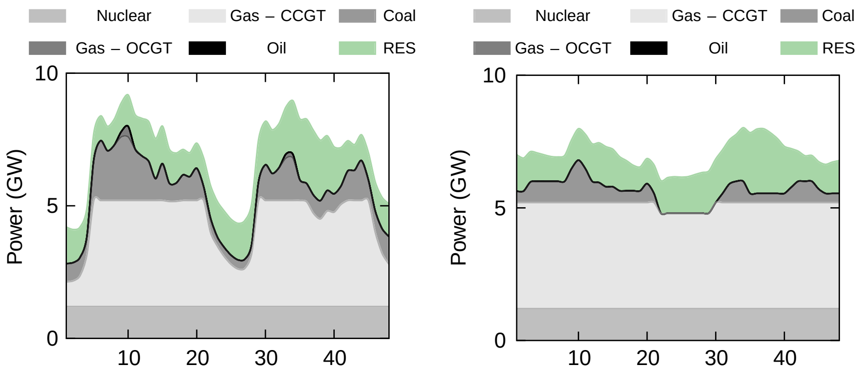

Fig. 7 Case Study B. Output of the electricity generation system (open cycle gas turbines (OCGT), combined cycle gas turbines (CCGT), and renewable energy sources (RES), coal, oil, nuclear) for two shares of DR participation rate: (A) 0% and (B) 100%. Inspired by Patteeuw D, Bruninx K. Arteconi A, *et al.* Integrated modeling of active demand response with electric heating systems coupled to thermal energy storage systems. App Energy 2015;151:306–19.

facilities. Indeed, the electricity generation system consists of a wider variety of technologies (nuclear power plant, coal fired steam power plants, CCGT, OCGT, and RES). The nuclear power plants, followed by gas fired CCGT plants cover the baseload residual demand, and gas fired OCGT plants are used as peaking units. Going from the normal operation of the power system without DR (Fig. 7(A)) to the power system including DR programs with a 100% participation of the potential flexible electrical demand (Fig. 7 (B)), valley filling during nighttime and load shifting during peak hours occur. The OCGT plants that cover the peak residual demand are no longer switched on during the considered simulated period.

As a result of such behavior, the cost of electricity generation is reduced, because more efficient power plants work for longer time periods. Consequently, these units set the electricity price during more time steps, which results in a lower electricity price (on average).

In Fig. 8 the trend of the power system relative operational costs, Rc, is shown. Rc is defined as the ratio between the total operation costs (TOC) with DR and the total operational cost in case of no DR participation [63]. Fig. 8 shows a reduction of the relative operational costs up to 2% of the TOC. It is a small percentage, but the absolute value can be very big. Note that these numbers are highly case study dependent (see Section 5.4.6.3). However, it has been shown by Arteconi *et al.* [63] that the economic benefit for a single user can be limited, thus a detailed cost-benefit analysis from customers' point of view (considering investment costs for smart thermostats, reduced energy bills, indoor thermal comfort experienced) is necessary when a DR strategy is designed.

The costs trend in Fig. 8 reflects the increasing flexibility induced by a growing adherence of the considered final users to DR programs. This flexibility allows for (1) a more efficient operation of the available electricity generation capacity (as explained above) and (2) a higher utilization rate of the available RES based generation. Fig. 9 shows the RES curtailment as a function of the DR penetration rate: it reduces from 3% to about 1% going from a 5% DR penetration rate to 100% penetration rate [63].

As described in Section 5.4.2.2, the REDR indicator, pertinent in this evaluation, would increase accordingly to the DR participation. Considering a higher RES share in the generation mix, the flexibility of the demand also gains more relevance (see Section 5.4.6.3).

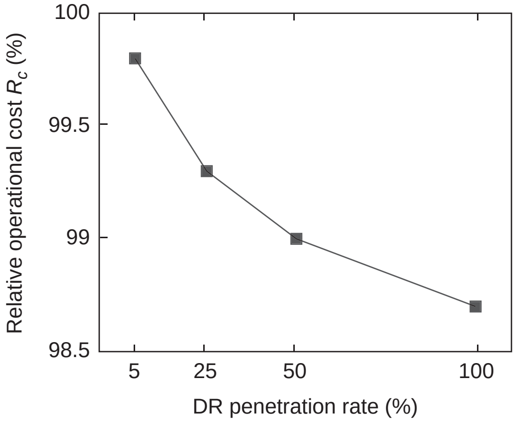

Fig. 8 Case Study A. Relative operational costs by varying the demand response (DR) participation rate. Inspired by Arteconi A, Patteeuw D, Bruninx K, *et al.* Active demand response with electric heating systems: impact of market penetration. App Energy 2016;177;636–48.

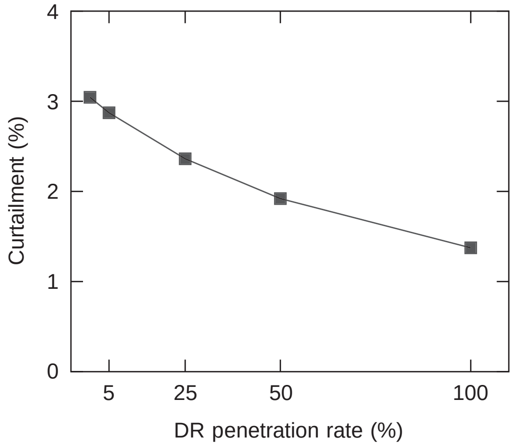

Fig. 9 Case Study A. Renewable energy sources curtailment by varying demand response (DR) participation rate. Inspired by Arteconi A, Patteeuw D, Bruninx K, *et al.* Active demand response with electric heating systems: impact of market penetration. App Energy 2016;177:636–48.

Fig. 10 shows the DRR ratio versus the DR penetration rate for different RES shares. The DRR ratio is defined as the ratio between the observed electric energy use by the flexible electric heating systems and the minimum electric energy use of those heating systems ($p^{\mathrm{DR}} = 0\%$) [63]. DRR is always greater than or equal to 1 because when there is a DR program in place, the electric demand is shifted (e.g., a preheating of the building or DHW tank is requested) and load shifting leads to higher temperatures in the building and in the DHW storage tank. Consequently, additional thermal losses and an increase in overall energy use occur. Higher values of DRR indicate that the flexibility offered by the buildings involved in the DR program is bigger on a per-building basis. Fig. 10 highlights that for higher RES share, more flexibility is necessary. This confirms once again that a power system with more intermittent electricity production benefits more from a flexible demand that can contribute to strengthen the reliability of the overall system.

5.4.6.2 Demand Response Related to Adequacy: Peak Shaving

As already discussed in the previous section, the electric heating system in buildings can be leveraged to provide power system flexibility that allows shifting the energy demand from peak hours to off-peak hours. Such scheme may be used to improve the adequacy of a power system by peak shifting or peak clipping. Fig. 11 shows the peak shaving produced by DR in the considered Case Study A and links the peak shaving capability to the DR penetration rate among participants. The peak shaving potential has been quantified during the coldest winter week, when the power system is stressed the most and the electric power demand, especially for electric heating purposes, is the highest. It amounts at most to 2 GW for this case study [63], which is equal to about 12% of the total installed capacity. Similarly, the peak shaving potential increases with a higher participation in the DR programs. Actually, the peak residual demand decreases strongly if the DR penetration rate is lower than 50% and flattens when the DR penetration grows beyond this threshold. This effect has been referred to as a saturation effect. It illustrates that the power system

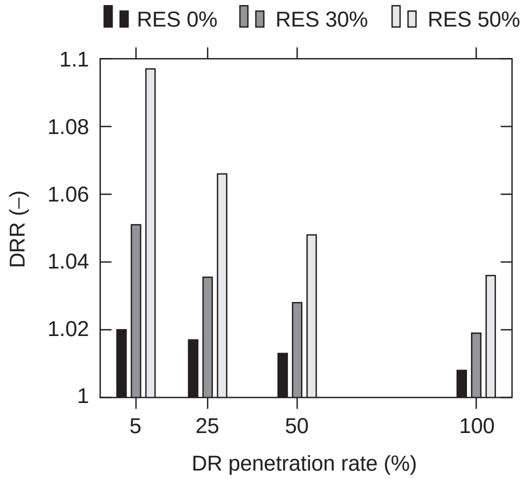

Fig. 10 Case study A. Demand recovery ratio (DRR) by varying the demand response (DR) participation rate for different renewable energy source (RES) shares. Inspired by Arteconi A, Patteeuw D, Bruninx K, *et al.* Active demand response with electric heating systems: impact of market penetration. App Energy 2016;177:636–48.

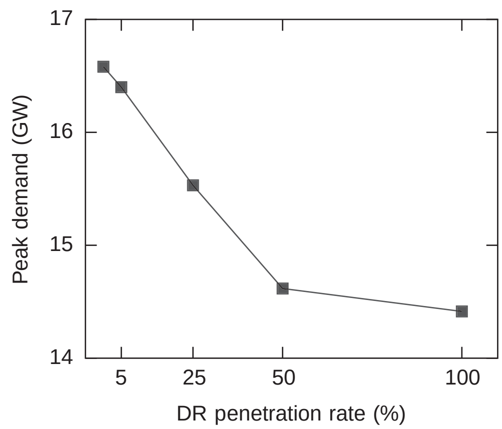

Fig. 11 Case Study A. Peak residual demand by varying the demand response (DR) penetration rate. Inspired by Arteconi A, Patteeuw D, Bruninx K, *et al.* Active demand response with electric heating systems: impact of market penetration. App Energy 2016;177:636–48.

needs and uses the flexibility provided by the customers (in this case by electric heating systems in buildings), but after a certain limit the additional flexibility available is less useful and cannot be fully exploited due to the limited load shifting potential of the DR resource. This means that when more participants are involved in the DR program, a lower effort per participant is requested (i.e., lower load shifting), but at the same time also the benefits perceived by each customer are reduced [63].

The reduction of peak demand implies a reduction in the use of peaking generation units (i.e., OCGT in Case Study A). This affects also the electricity price, which decreases accordingly. In **Fig. 12** the duration curve of the electricity price for the scenarios with DR = 0% and DR = 100% is represented. The effect produced on price by peak shaving is highlighted in the figure: the peak price duration time is diminished by about 2000 h.

Eventually, it is important to point out the influence of the building type and heating system configuration (i.e., distribution system) involved in the DR program on the peak power demand. This effect is illustrated by means of Case Study C and is shown in **Fig. 13**. When electric heating systems are introduced in buildings to replace traditional heating system (e.g., boilers), the overall electricity demand for a building increases. Due to possible concurrence of such building electricity demand with the fixed electricity demand (d^{fix}), even the peak power demand of the overall system increases. In **Fig. 13**, it is demonstrated that the additional peak power per building is limited when those buildings participate in DR. This confirms once again the peak shaving potential of heat pumps adhering to DR programs, thus their effect on power system adequacy. **Fig. 13** highlights also that the peak shaving ability is higher for HPs with lower nominal electric power demand, because, considering Case Study C, they are installed in buildings with better thermal insulation and floor heating systems, allowing lower thermal losses and longer load shifting due to their larger thermal inertia.

In the scientific literature, other studies analyzed the peak shaving potential of different DR programs. In Ref. [72], for example, the Iranian power system is investigated and it is shown that DR can reduce the peak demand in a range between 6 and 10%,

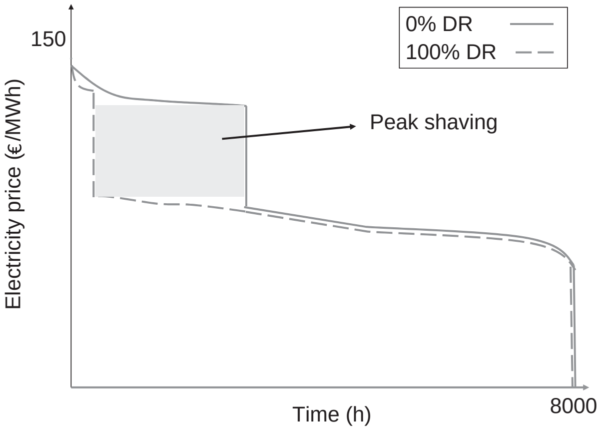

Fig. 12 Case Study A. Electricity price duration curve for the case with demand response (DR) participation rate at 0 and 100%. The shifting between the two curves is due to the peak shaving effect. Inspired by Arteconi A, Patteeuw D, Bruninx K, *et al.* Active demand response with electric heating systems: impact of market penetration. App Energy 2016;177:636–48.

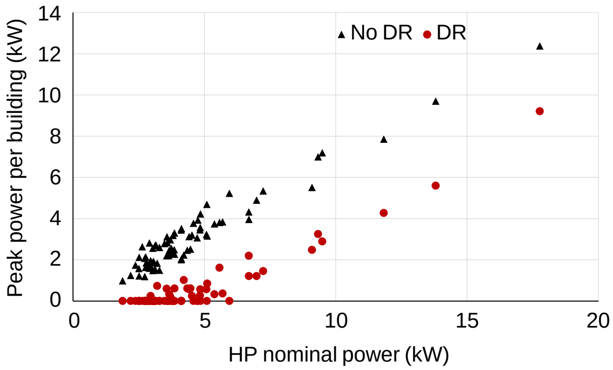

Fig. 13 Case Study C. Additional peak power demand per building produced by the replacement of conventional heating systems with electric heating systems (HPs) by varying the heat pump nominal power demand for the case without demand response (DR) (0%) and with DR (100%). Inspired by Patteeuw D, Reynders G, Bruninx K, *et al.* CO_2-abatement cost of residential heat pumps with active demand response: demand- and supply-side effects. App Energy 2015;156:490–501.

considering an installed peak power of about 33 GW. The DR peak shaving potential is of paramount importance for improving the power system adequacy. DR guarantees the necessary flexibility of the demand side during periods of peak demand or system distress, reducing the required investments in new dispatchable power plant capacity without increasing the risk of load shedding. However, the DR program has to be properly designed. Indeed Samadi *et al.* [71] showed that erroneous formulations of DR tariff structures could give rise to an increase in the peak demand and this affects the EENS negatively, thus the reliability of the power system is decreased. When, instead, a peak reduction is achieved, the benefit in terms of reduction of electric energy not served is evident. In their case study with an initial peak load of 2850 MW, a 5% reduction of peak, due to a TOU tariff based DR, leads to a 25% reduction of EENS.

5.4.6.3 Demand Response Related to Security: Reserve Provision

For the discussion of the possible benefits associated with DR based regulation services or reserves (i.e., operational flexibility), a set of results from Bruninx *et al.* [5,87] is reproduced below. The purpose of this analysis is to show how the different available flexibility providers (DR, spinning reserves, nonspinning reserves, and energy storage) interact. The developed model allows studying the operational costs that a system operator incurs to meet the demand for electricity, while maintaining power system security. The focus is on the interaction between operational costs, reserve provision (security), and DR resources. Indeed, in real-time operation it can be cost-efficient to exploit the flexible demand in order to mitigate the impact of a contingency or the unpredicted behavior of RES based generation. The operational model specifically allows scheduling DR resources, in this particular case study electric heating systems, as reserves, while simultaneously guaranteeing the thermal comfort of the owners of the DR resource.

Case Study D has been considered, using a state of the art UC model for the representation of the supply side, considering reserve constraints to account for the limited predictability of RES based generation. The reliability of the obtained electricity

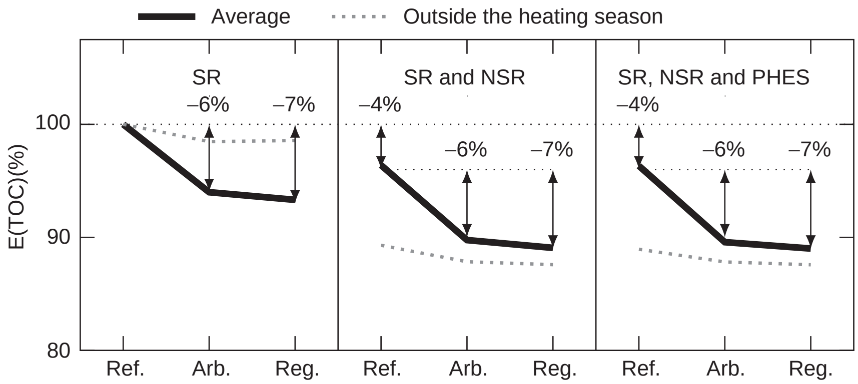

Fig. 14 Case Study D. Expected total operational costs for 3 unit commitment (UC) strategies (SR, SR&NSR, SR, NSR&PHES) considering 3 different demand response (DR) settings (Ref. = No DR; Arb. = arbitrage services; Reg. = arbitrage & regulation services). The analysis is performed for an average week in heating season and for a week outside heating season Inspired by Bruninx K. Improved modeling of unit commitment decisions under uncertainty [Ph.D. thesis]. KU Leuven; 2016.

generation schedules with respect to this uncertain RES based generation is tested in Monte Carlo ED simulations, leveraging the flexibility at the demand side and the supply side.

In this analysis of the system value of DR based arbitrage and regulation services, three UC strategies are considered. In the SR case only spinning reserves (i.e., online reserves) may be scheduled. In the SR and NSR case additionally nonspinning reserves (i.e., offline or standing reserves) are available to meet the reserve requirements. In the case of SR, NSR and ES, spinning, nonspinning, and ES based reserves are available. For each of these UC strategies, the expected total operational cost (E(TOC)), the expected wind utilization factor (E(WUF)), the resulting total demand (E(Load)), the share of electrical energy generated from non-renewable resources (1-E(WS)), and EENS in three DR settings are calculated. The DR settings are the following:

1. In the reference case (Ref.), the DR capable load is not responsive. The electricity demand of the electric heating systems is fixed to a minimum energy use profile (see Section 5.4.4.1);
2. The DR capable heating systems are only used for arbitrage purposes (Arb.), i.e., load shifting aimed at reducing operational costs, under forecast conditions;
3. Both arbitrage and regulation services may be procured from the DR load (Reg.), i.e., also reserve provision for security purposes is considered.

Results are presented for (1) a week outside the heating season and (2) an average week (based on simulations of 4 weeks, properly selected to represent the whole year) [5,87].

Significant cost savings are to be expected from DR based arbitrage and regulation services (**Fig. 14**). On average, the operational cost decreases by 6 percentage points (pp) when considering DR based arbitrage (Arb., **Fig. 14**). An additional one percentage point decrease can be realized when the DR adherent loads are also allowed to provide regulation services (Reg., **Fig. 14**). The reliability of the resulting UC schedules is unaffected: the EENS is at most 0.0004% of the total load and does not vary significantly across the considered DR cases.

Remarkably, the value of DR based arbitrage and regulation services remains unaffected when other flexibility providers, here nonspinning reserves and ES based reserves, are available to meet the reserve requirements. Indeed the presence of these flexibility providers, in particular nonspinning reserves, does decrease the operational cost (on average 4 pp), but does not affect the value of DR based arbitrage and regulation services. Outside the heating season, the demand of the electric heating systems, thus the available DR flexibility, is significantly lower. The operational cost decrease resulting from DR based arbitrage and regulation is limited (max. 2 pp). Allowing nonspinning reserves and PHES based reserves results in an expected operational cost decrease of 11% outside the heating season.

The main driver of these cost reductions is an increased utilization of the available wind power (**Fig. 15**) and a more efficient scheduling and dispatching of the conventional power plants. On average, the WUF increases from 74.9–77.5% (Ref.) to 82.1–84.2% (Arb.) to 83.4–85.3% (Reg.). This increase of WUF is the result of (1) shifting demand to periods of excess wind power generation and (2) increasing the DR adherent demand to increase the indoor temperature in order to allow the DR adherent heating systems to provide upward reserves. This increase in indoor temperature (under forecast conditions) allows activating DR based reserves without tampering with the thermal comfort of the homeowner providing this flexibility. This does, however, increase the total demand as a result of increased thermal losses and a higher average indoor temperature (**Fig. 16**). The average increase in total demand amounts to 2.5% (ES, Arb.) and to 3.2% (SR, Arb., Reg.). The availability of nonspinning and ES based reserves limits the increase in demand, as less excess wind power is available to be absorbed by the DR adherent heating systems (**Fig. 15**).

On the contrary, the consideration of DR based reserves typically increases the total demand due to the higher indoor temperatures required to provide (upward) reserves. As a result, the share of nonrenewable energy sources in the fuel mix (**Fig. 17**)

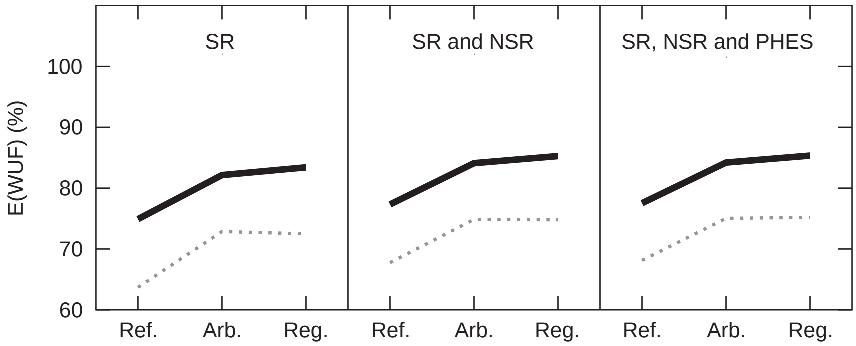

Fig. 15 Case Study D. Wind utilization factor (expresses as a percentage of the available wind energy) for 3 unit commitment (UC) strategies (SR, SR&NSR, SR, NSR&PHES) considering 3 different demand response (DR) settings (Ref. = No DR; Arb. = arbitrage services; Reg. = arbitrage & regulation services). The analysis is performed for an average week in heating season and for a week outside heating season. Inspired by Bruninx K. Improved modeling of unit commitment decisions under uncertainty [Ph.D. thesis]. KU Leuven; 2016.

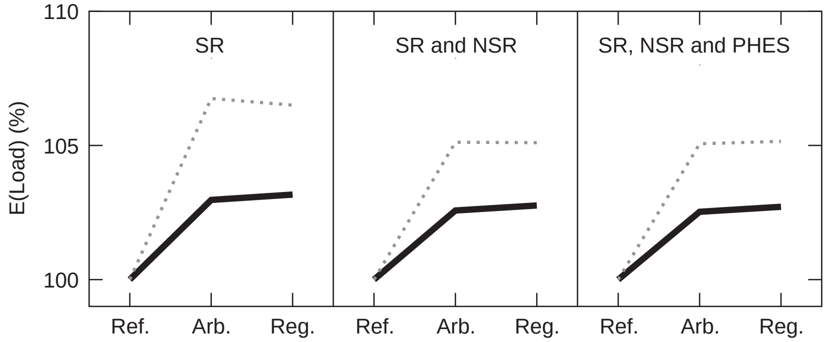

Fig. 16 Case Study D. Total demand for electrical energy for 3 unit commitment (UC) strategies (SR, SR&NSR, SR, NSR&PHES) considering 3 different demand response (DR) settings (Ref. = No DR; Arb. = arbitrage services; Reg. = arbitrage & regulation services). The analysis is performed for an average week in heating season and for a week outside heating season. Inspired by Bruninx K. Improved modeling of unit commitment decisions under uncertainty [Ph.D. thesis]. KU Leuven; 2016.

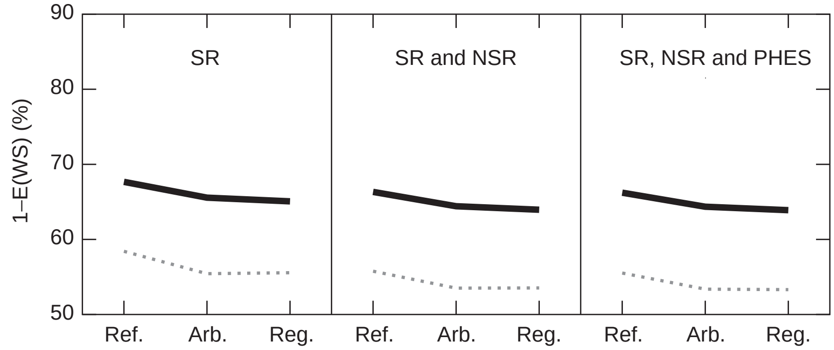

Fig. 17 Case Study D. The share of the demand covered by nonrenewable sources for 3 unit commitment (UC) strategies (SR, SR&NSR, SR, NSR&PHES) considering 3 different demand response (DR) settings (Ref. = No DR; Arb. = arbitrage services; Reg. = arbitrage & regulation services). The analysis is performed for an average week in heating season and for a week outside heating season. Inspired by Bruninx K. Improved modeling of unit commitment decisions under uncertainty [Ph.D. thesis]. KU Leuven; 2016.

does not decrease as fast as the WUF increases. On average, 67.7–66.2% of the demand would be satisfied with electricity generated from non-RES in the absence of DR. This drops to 65.6–64.4% and 65.1–63.9% when considering DR based arbitrage and regulation, respectively.

In conclusion, DR allows maintaining system reliability at a reduced operational cost, even at high RES penetration rates. If thermal discomfort is not allowed, these operational cost savings can be almost fully attained by leveraging DR loads to perform arbitrage. This will allow other resources to cost effectively fulfill the reserve requirements, which may limit the additional value in

DR based reserves. Allowing thermal discomfort may increase the attainable operational cost savings via DR based reserves [5,87]. However, the operational cost savings may not justify the impact on thermal comfort for end consumers [5,87].

Other authors evaluated the effect of DR programs on short-term reliability. In particular, in Ref. [74] the contribution of DR together with wind power plants to the system reliability is also quantified. As maximum these authors allow an incremental peak load carrying capability (defined as the increase in peak load to reach the same level of risk as before their introduction) of about 10 MW, assessed by means of loss of expected energy for the case of peak demand 185 MW and wind power installed 20 MW. In Ref. [31], instead, the reliability improvement on the distribution network is analyzed, considering the reserve provision by DR programs, allowing to shift the demand after the service, interrupted by a contingency, is restored. Part of a real Finnish network with 61 distribution substations is considered. On the basis of the contingency, the energy not served can be diminished at different levels with a maximum up to 90%.

5.4.6.4 Methodological Improvements: Demand Response Limited Controllability

The relevance of DR with electric heating systems to improve the reliability of a power system has been demonstrated by means of the case studies described in the previous sections. The integrated model considered contains some simplifying assumptions that do not affect the general results obtained. However, such simplifications could prevent to take into account possible particular issues related to the introduction of DR programs. For example, the effect of a possible imperfect controllability of DR resources is an important aspect to evaluate, because not all the components of the power system are equally controllable. Bruninx *et al.* [87] use chance constrained programming to account for the possible variability in the response of DR loads. In this approach the deterministic variable that represents the energy demand from flexible electric heating systems (see Eq. (29)) becomes a stochastic variable. Bruninx *et al.* assume this stochastic variable can be modeled as a disturbance on the original DR demand. This disturbance is assumed to consist of a non-proportional disturbance (δ^{NP}) that follows a Normal distribution (Eq. (32)):

$$\hat{d}_j^{H,\mathrm{var}} = d_j^{H,\mathrm{var}} + \delta^{\mathrm{NP}} \tag{32}$$

The scheduled generation capacity does not coincide exactly with the expected demand, but has to exceed the demand with a certain mark-up, so that the obtained schedule allows meeting each real time realization of the demand with a given probability ($1-\varepsilon$), which is an indicator of the risk attitude of the system operator. Bruninx *et al.* [87] used Case Study D to test their expanded model to investigate the influence of limited controllability of DR loads on the expected operational cost, RES utilization and reliability. In their case study, they assume that DR is only used for arbitrage and DR controllability is represented by means of a non-proportional term (δ^{NP}) with a zero mean and three possible standard deviations (σ^{NP}): 50, 100, and 250 MW. Results show that if the variability of DR adherent loads is limited, the possible cost savings produced by DR in case of perfect controllability do not decrease significantly. Instead, if the system operator is risk adverse (ε->0) and the expected variability in the DR adherent load is high, the operational costs of the power system may be increased by the introduction of DR. This is due to the necessity of more scheduled capacity, which leads to a less efficient dispatch of the scheduled units and a reduced utilization of RES based generation. If a system operator, however, approaches risk-neutral behavior (ε->0.5), the obtained schedule may not allow meeting the load in all RES based generation and DR scenarios. This is illustrated in **Fig. 18**, which shows the electric energy not served as function of the risk attitude of the system operator ($1-\varepsilon$): when the risk attitude is bigger, then the possibility of not satisfying the energy demand is higher and the EENS increases.

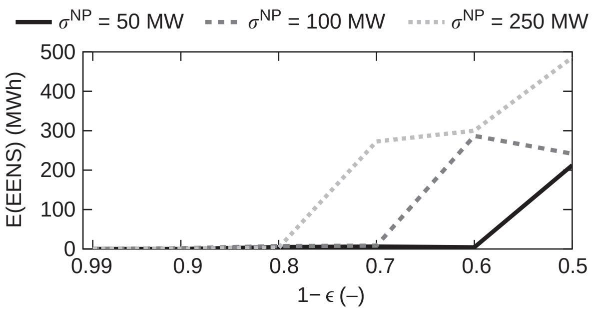

Fig. 18 EENS in case of limited controllability of demand response for different risk policies of the system operator ($1-\varepsilon$). The analysis refers to an average week in heating season (the same as specified in Section 5.4.6.3). Three different normal distribution for the nonproportional (δ^{NP}) component of the electric heating systems energy demand stochastic variable are considered with zero as mean value and standard deviation (σ^{NP}) equal to 50, 100, and 250 MW. Inspired by Bruninx K, Dvorkin Y, Delarue E, D'haeseleer W, Kirschen DS. The value of demand response controllability, KU Leuven Energy Institute Working Paper WP EN2017-03. Available from: http://www.mech.kuleuven.be/en/tme/research/energy_environment/Pdf/wp-en2017-3.pdf; 2017.

5.4.6.5 Comparison With Other Approaches for Increasing Reliability

In this section the capability of improving power system reliability by other methods rather than DR is illustrated. As outlined previously, there are different techniques to be used on the supply side or on the demand side to put energy management strategies into action (see Section 5.4.2.3). In the following, their potential on power system reliability is quantified by means of case studies presented in the scientific literature. In detail:

1. DR versus EES systems: the effect of DR on power system reliability is compared with the effect produced by EES systems installed on the supply side, in order to highlight their differences in operation;
2. Energy storage: the potential of improving reliability by EES systems and their optimal planning is further investigated when they are situated on the distribution network or on the generation level;
3. Distributed generation: the role of DG units for reserve provision is considered;
4. Electric vehicles (EV): EV as instruments for increasing the operational flexibility, thus augmenting reliability, of a power system are also investigated; and
5. Incentives: the influence of incentive policies to boost the best strategies to optimize power system reliability is reported.

5.4.6.5.1 Demand response versus electric energy storage system

Zhou *et al.* [30] compare the contribution of DR and EES to the adequacy of supply. They consider different kinds of controllable loads, represented with existing load profiles without including any physical description. However, they take into consideration the load restoration issue (i.e., payback) through predefined payback coefficients. Moreover, different DR scenarios with four different payback effects are considered (no payback, unconstrained payback with load fully restored, constrained payback with load half restored, constrained payback with load fully restored). Instead, the EES is represented without any reference to a specific type of storage, but using its operating parameters (energy capacity, power rating, efficiency). The model optimizes the power system in order to minimize the peak load. The adequacy of the supply is evaluated by means of the indicators LOLE, EENS, LOLF, and LOLD. Results show that both DR and EES contribute positively to the system reliability but in a different manner. Regarding DR, with the same payback setting, LOLE, EENS, and LOLF decrease with the increase of customer's flexibility (a certain saturation effect is also evident after a certain flexibility level). For different scenarios, when the payback is less constrained the effect on adequacy is stronger, because there is a reduced risk of creating another peak load. LOLD, instead, increases with DR. This is due to the stretch of the peak load: if a shortfall event occurs during this period, its drawbacks could be even more severe. As far as the EES is concerned, the use of energy storage causes a decrease of LOLE, EENS, and LOLF. The main parameter to be taken into account is the power rating, which poses the limit to the maximum energy capacity necessary: beyond a certain limit a saturation effect occurs, because storage with a given power rating cannot use more than a given energy capacity when it shifts peak energy demand to off-peak hours. Or it can happen that the given power rating is not enough to charge the ESS fully during off-peak periods. Also the increased storage efficiency produces benefits on the adequacy up to the limit that equals the peak reduction to the storage power rating (as explained above, the peak reduction cannot be bigger than the power rating). In both cases it is not possible to displace as much generation as the peak reduction provided by DR or EES, if the original level of adequacy needs to be maintained. The results presented in this paper show that the ability to perform peak shaving by means of DR is more effective than that provided by EES in terms of MW curtailed (about 1000 vs. 500 MW for the case study considered [30]), but results are case sensitive and a generalization is difficult.

5.4.6.5.2 Energy storage

Sabori *et al.* [35] consider the use of ESS to augment the reliability of a distribution network (HL3). In this work, the optimal size and place for EES in a radial electrical distribution network that allow the minimization of the electric energy not served are studied. The methodology proposed is applied to a case study, composed of an 11-kV and 30-bus radial distribution network with different-capacity EES to be installed on 15 buses. Results show that EENS can be reduced with respect to the case without EES of 33%, while the total operation costs decrease by about 10%.

Bruninx *et al.* [89] develop a set of constraints to allow optimal EES based reserve scheduling in deterministic and improved interval UC models. In a case study, inspired on the Belgian power system assuming a high RES penetration, they show that EES based reserves lead to significant operational cost savings without reducing the reliability of the obtained UC schedules.

5.4.6.5.3 Distributed generation

Sabpayakom and Sirisumrannukul [90] investigate the role of very small power units (<10 MW) to improve power network reliability. In the case of radial and single circuit distribution networks, the risk of not being able to serve some users when contingencies occur is relevant. DG can be used as an operational reserve to provide electricity to the disconnected segments of the grid during contingencies, thus the network becomes an active element able also to improve the reliability of the power system. The small power units can reduce the outage duration when an islanding operation of the disconnected network is possible and the unit is within the islanded area. A case study is defined by the authors to show the effects of DG on reliability: it is inspired to an urban 24-kV distribution system in Thailand with 34 customer load points and a DG of 2 MW is connected to the middle of a branch. Results show the role of small DG under different point of views: (1) capacity: the network reliability indices (SAIDI, EENS and outage duration time) are improved; (2) size: the reliability benefits more when the size of the power unit increases, but it is

necessary not to exceed the demand otherwise reverse power flows toward the transmission grid occur and it could cause additional problems; (3) connection point: the position of the DG has to allow picking up some loads, preferably it has to be close to the end of the feeder; (4) number of units: generally increasing the number of DG improves the system reliability, but it depends also on the interaction between the supply and demand in the isolated areas.

5.4.6.5.4 Electric vehicles

Bozic and Patos [91] analyze the impact of EV on power system reliability. This is an issue frequently discussed in the scientific literature and several studies highlighted the potential role of EV as ancillary service or frequency regulation provider, thanks to their inherent electric battery storage system. In [91] it is investigated in particular to what extent such EVs can contribute to the power system reliability and the influence of the selected charging/discharging strategy on this contribution. Such strategy is determined by means of an optimization problem that minimizes the reliability indices LOLE and EENS. It is shown that the introduction of EV brings a benefit to the reliability of the system up to a certain number of vehicles, afterward the reliability indices increase again. In the case study considered by the authors, 68,750 vehicles as maximum are taken into account with a battery capacity of 25 kWh each and a charging and discharging efficiency of 90 and 93%, respectively. Full charge and discharge phases take 2 h and the discharging conversion factor is 6 km/kWh. Results highlight that 31,950 vehicles optimize the reliability of the power system, but the users have to be rewarded by an incentive because this configuration does not minimize the transportation costs. Thus, in order to have reserve provision by EV, it is necessary to have a compensation on average of 1.00 cEUR or 1.85 cEUR per 100 km per each EV if, respectively, LOLE or EENS need to be reduced by 1%.

5.4.6.5.5 Incentives

Ibanez-Lopeza *et al.* [92] consider the effect of different incentive schemes on the power system reliability. They use a so-called system dynamics model to assess the technical, economic, and environmental impact of renewable energy incentives and capacity payment policies. The analysis is referred to the Spanish power system, where the need for adequate reserve margins that guarantee reliability is highlighted. Main results obtained are here summarized: (1) capacity payments: increased capacity payments for base load technologies allow an increased system reliability, with limited increase in CO_2 emissions, but cause also a consistent growth of the total costs; (2) alternative energy incentives: more renewable energy in the generation mix significantly reduces CO_2 emissions, however, it is not able to secure more reliability. Even in this case costs are bigger than in the base case scenario without incentives, because the increased wind power capacity considered by these authors reduces the capacity margins and produces wind price spikes, negatively affecting the overall system costs. This confirms what other authors stated about the necessity of ESS on the supply side to favor the renewable energy integration in the generation mix in order to maintain proper reliability levels [42].

5.4.7 Future Directions

In this work the relationship between reliability of a power system and DR programs has been discussed and demonstrated. While it is evident that such relationship exists and DR can be beneficial for the system adequacy and security, it is not easy to quantify the DR impact exactly.

In the scientific literature, different studies are available, but all of them have different assumptions and, necessarily, contain some simplifications that make difficult to take into account all possible influencing variables and phenomena. Indeed, while some papers highlight only positive effects on the reliability due to the introduction of DR, other works point out possible drawbacks, such as those related to the restoration of the load after a DR event that could cause even worse conditions on the system. Furthermore, it is very difficult to find modeling tools that represent the generation side, the network, and the demand (including different kinds of loads with different behaviors) in a detailed way. This aspect limits the ability to quantify thoroughly the influence of DR on reliability.

As far as the model presented in this piece of work is concerned, it has as its strength the ability to represent both the supply side and the demand side with a good level of detail in an integrated way that allows taking into account their interactions. Nevertheless, it would be necessary to include also the transmission and distribution network in the model, thus to assess both the reliability at all hierarchical levels by means of proper reliability indices. The effect of uncertainty on the production side (RES) and on the demand side (users' behavior, etc.) should be further investigated and included in the model by means of probabilistic simulations, as already outlined in Section 5.4.6.4. Other DR loads could also be added (e.g., domestic appliances, EV, etc.). Only in this way it will be possible to provide a comprehensive evaluation of the actual relationship between reliability and DR.

5.4.8 Closing Remarks

Key points of this contribution are listed below:

- A strong correlation between reliability and energy management to increase system adequacy and security has been demonstrated.
- DR is a good instrument, within demand side energy management strategies, to increase power system reliability.

- DR is beneficial for reliability thanks to its ability to shift loads. Indeed, it allows reducing RES curtailment and using in a more efficient and effective way the existing generation capacity.
- DR increases the power system adequacy by means of peak shaving. This implies a reduced need for new generation capacity and decreased risk of load shedding.
- DR increases the power system security by means of its arbitrage and regulation services potential, which provides a flexible reserve for short term operation.

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The International Institute of Energy Systems Integration.